Information Visualisation to Support Informed Decision-Making under Uncertainty and Risk

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Mohammad Kamel Younis Daradkeh

Department of Applied Computing
Faculty of Environment, Society and Design
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Informed decision-making (IDM) depends on the availability of adequate information and the ability of decision-makers to manipulate this information. More often than not, the information on which decisions are based is subject to variability and uncertainty arising from different sources. Consequently, risk accompanies decisions as there is a chance that the decision taken can lead to an undesirable rather than a desirable outcome. Ignoring uncertainty and its associated risk may simplify the decision-making process, but it does not lead to making informed decisions. Thus, they should be explicitly considered from the beginning of the decision-making process as an integral part of the information on which decisions are based. Information visualisation (InfoVis) can play an important part in assisting people to make informed decisions under uncertainty and risk. It provides an effective means for depicting information in ways that make it amenable to analysis and exploration. It also can facilitate the integration of uncertainty into the decision-making process and raise the awareness of decision-makers about its effects.

This thesis presents the design and evaluation of a new InfoVis tool to support informed decision-making under uncertainty and risk. First, the information requirements and main considerations underpinning the design and evaluation of the InfoVis tool presented in this thesis have been identified. Second, an InfoVis tool for portraying information about the decision problem and raising the awareness of decision-makers about the uncertainty and risk associate with decision-making, called VisIDM, has been designed and implemented. VisIDM consists of two main parts: Decision Bars and Risk Explorer. Decision Bars provide overview information of the decision problem under uncertainty and risk through three panels: the Outcome, Risk, and Likelihood Bars. Risk Explorer provides decision-makers with a multivariate representation of uncertainty and risk associated with the decision alternatives. It facilitates the interactive analysis and comparison of available alternatives, either consecutively or simultaneously, at different levels of detail. Third, the usefulness of VisIDM for assisting people to make informed decisions has been evaluated through a qualitative user study. The study has also investigated how VisIDM was used by participants and what features support their exploration and perception of information.

The results of the study suggest that VisIDM is a useful tool for assisting people to make informed decision under uncertainty and risk. It provides them with a variety of information and assists them in performing several operations to arrive at their final decisions. It also raises people's awareness of the uncertainty and risk associated with decision-making and facilitates their analysis and exploration at different levels of detail. The results also show that although different types of information that people may need to make their decisions are presented in VisIDM, they tend to rely on a single or small number of salient pieces of information rather than on a systematic consideration and evaluation of all available information. In addition, people have problems in understanding and interpreting the uncertainty and risk information. In particular, they have a tendency to ignore the importance of probability information and rely, in large part, on the consequences of undesirable outcomes to form their impression about the risk. Moreover, the availability of information may not contribute greatly to people's feeling of increased confidence that they can make informed decisions. Rather, their ability to manipulate and comprehend information would enhance their confidence to make informed decisions.

Keywords: Information visualisation, Informed decision-making, Decision-making support, Uncertainty, Risk, Probability, Risk analysis, Risk perception, Sensitivity analysis, Uncertainty visualisation, Risk visualisation, Sensitivity analysis visualisation.

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CHAPTER 1
INTRODUCTION

1.1 Motivation

Decision-making is one of the central activities of human beings as situations that require making decisions constantly arise in almost all endeavours of their lives. All decisions, whether personal, business, or professional, are likely to bring about some future benefits to someone or something and involve choices. Some decisions such as which company's shares to buy, involve making a choice among multiple alternatives while others such as whether or not to invest in a new product are more "yes/no" decisions. Whatever the type of decision, the information available is considered a key element in the decision-making process, as it provides the basis for making informed decisions (Bekker, 2003). An informed decision is one where a reasoned choice is made by a reasonable individual using relevant information about the advantages and disadvantages of all the available alternatives (Bekker *et al.*, 1999).

In order to make informed decisions, people must not only have adequate and relevant information, but also be able to process this information in a way that is consistent with their objectives and preferences (Robinson & Thomson, 2000). One major obstacle of informed decision-making is that people are constrained by their limited information processing and cognitive capabilities (Simon, 1991). Hence, even if they have all necessary information, they don't usually use it all in decision-making. Rather, they often adopt simplifying strategies to ease the burden of information processing, and consequently base their decisions on a salient subset of available information (Kahneman & Frederick, 2005; Simon & Houghton, 2003). For example, they may focus closely on one particular piece of information, say the extreme outcomes of available alternatives, but overlook their likelihood of occurrence.

Furthermore, ubiquitous in realistic situations, the information upon which decisions are based is often subject to variability and uncertainty arising from different sources. Typical sources include the lack of knowledge of true values of decision variables or parameters and future possibilities and outcomes. For example, the decision about whether to invest in a new product depends on the uncertain market conditions (e.g. whether the demand will go up or down). The possible outcomes of the decision (e.g.

making a profit or loss) are also dependent on how much the demand goes up or down and its interaction with other variables (e.g. the price of the product). In this situation, the decision-maker may evaluate the possible outcomes and their associated likelihood under different scenarios, and base his or her decision on this evaluation. Typically, not all possible outcomes are equally desirable to the decision-maker. Consequently, the decision made involves an undeniable amount of risk because there is a chance that it may result in an undesirable rather than a desirable outcome.

Ignoring uncertainty may simplify the decision-making process, but it does not lead to making informed decisions. Thus, the uncertainty and its associated risk should be explicitly considered from the beginning of the decision-making process as an integral part of the information on which decisions are based. However, the integration of uncertainty and risk into the decision-making process poses significant cognitive challenges. It brings additional complexity and confusion to the task of decision-making which is already complicated. One example of such confusion occurs when comparing or ranking multiple alternatives, each with a range of possible outcomes. Furthermore, the process of integrating uncertainty and risk into the decision-making process is a highly technical subject, and often not transparent or easy to grasp by decision-makers not trained in this methodology.

All these problems — uncertainty, risk, and limited information-processing and cognitive capacity— will not simply disappear because of the incremental advances in the technology available to human decision-makers. The crux of the problem is that these problems are human-centric. Thus, their resolution will not occur by replacing humans in the decision-making process, but rather by supporting them with technological aids that can expand their abilities and strengthen their inherent weaknesses of information-processing and cognitive capabilities.

One technology that has emerged as a vital aid to judgement and informed decision-making is information visualisation (InfoVis). It provides an effective means for depicting information in a way that makes it amenable to analysis and exploration. It can facilitate the integration of uncertainty into the decision-making process, and raise the awareness of decision-makers about its effects. Moreover, it can enhance the ability of decision-makers to manipulate and comprehend information, thereby making more informed decisions (Tegarden, 1999; Zhu & Chen, 2008).

Over the past two decades, several InfoVis tools that claim to be helpful in decision-making have been developed in many different areas (Carenini & Loyd, 2004; Johnson & Shneiderman, 1991; Yi, 2008). In addition, some frameworks that seek to bridge the gap between the emerging area of information visualisation and cumulative knowledge of decision-making have been proposed (e.g., Bautista & Carenini, 2006; Yi, 2008). However, the majority of existing InfoVis tools were designed and applied based on the assumption that the information available to decision-makers is deterministic and certain. This assumption is rarely valid in practice; most real-world decision problems typically involve uncertainty which if not explicitly considered, can lead to poorly informed decisions.

Moreover, many of the existing InfoVis tools focus on presentation rather than interactive analysis and exploration of the decision problem and the uncertainty and risk it entails. Without interactive exploration of alternatives, the decision-maker may not fully appreciate the impact of uncertainty in the decision problem. According to the NIH/NSF visualisation research challenges report (Johnson *et al.*, 2005), an InfoVis system to support decision-making should allow ordinary people to assess changes, cause and effects, and experiment with "what-if" scenarios. The ability to analyse "what-if" scenarios is a key requirement for developing understanding about the implications of uncertainly, which in turn leads to making more informed and justifiable decisions (French, 2003).

1.2 Research objectives

The main objective of this thesis is to develop a new InfoVis tool and explore its potential benefits for assisting people to make informed decisions under uncertainty and risk. This objective is translated into the following main research question:

How can InfoVis tools assist people in making informed decisions under uncertainty and risk?

In order to answer the research question, the following tasks are carried out:

- Identify the main requirements and considerations that need to be addressed when designing InfoVis tools to support informed decision-making under uncertainty and risk.

- Design and implementation of new InfoVis tool for assisting people to make informed decisions under uncertainty and risk.
- Assess the usefulness of the InfoVis tool for assisting people to make informed decisions under uncertainty and risk.
- Explore how people interact with and perform tasks using the InfoVis tool to arrive at their final decisions.
- Explore what types of information people use to be better informed during the decision-making process.
- Explore the effect of the InfoVis tool on people's perception and interpretation of information presented.

1.3 Anticipated contributions

The anticipated contributions of this thesis are:

- An analysis and exploration of the information requirements and main considerations that need to be addressed when designing InfoVis tools to support informed decision-making under uncertainty and risk. These issues and considerations will provide a baseline and guidance for the design and evaluation of the InfoVis tools presented in this thesis.
- The design and implementation of a new InfoVis tool to support informed decision-making under uncertainty and risk. The intention of this tool is to enable the interactive analysis and exploration of alternatives at different granularities of detail. It is also intended to facilitate the integration of uncertainty and risk into the decision-making process and allow users to experiment with multiple "what-if" scenarios.
- A qualitative evaluation of the usefulness of the developed InfoVis tools for assisting people to make informed decisions under uncertainty and risk.

1.4 Thesis organisation

The remainder of this thesis is organised as follows:

Chapter 2 provides a background on decision-making and various aspects of uncertainty and risk associated with decision-making. Chapter 3 reviews the literature on information visualisation to support decision-making, and discusses the theoretical frameworks, InfoVis techniques, and evaluation studies that have been done in this area of research. The main contributions of this thesis are described from Chapter 4 to Chapter 8. Chapter 4 discusses the information requirements and main considerations underpinning the design of the InfoVis prototypes presented in this thesis. Chapter 5 describes the design and implementation of the InfoVis prototypes to support informed decision-making under uncertainty and risk. Chapter 6 describes the procedure employed in a study conducted to assess the utility of final InfoVis prototypes for assisting users to make informed decisions under uncertainty and risk. The results obtained from the study are presented and discussed in Chapters 7 and 8. Chapter 9 concludes this thesis with a summary of contributions and perspectives for future work.

CHAPTER 2
DECISION-MAKING, UNCERTAINTY AND RISK

2.1 Introduction

Decision-making under uncertainty and risk has been studied extensively by a wide range of different disciplines and from a number of different theoretical perspectives. As a result, various theories, approaches, and models that describe how decisions are actually, or should be, made under uncertainty and risk have been proposed. Providing an exhaustive review of this vast body of literature is simply not feasible (Lehto & Nah, 2006). At the same time, it is outside the scope of this thesis. Therefore, this chapter is not intended to present a comprehensive review, but rather to provide an essential background and insight into the main requirements and considerations that need to be addressed when designing InfoVis tools to support informed decision-making under uncertainty and risk.

This chapter begins by providing a brief overview of the concept of decision-making, followed by a broad classification of decision-making problems in Section 2.2. Section 2.3 provides an overview of the various aspects of uncertainty and risk in decision-making. Section 2.4 briefly reviews the main theories, models, and strategies of decision-making under uncertainty and risk. This section also discusses the common obstacles decision-makers face due to the presence of uncertainty and risk. Section 2.5 presents criteria essential for decision-making under uncertainty and risk to be considered as “good” or “better” decision-making. This chapter ends with a summary and discussion in Section 2.6.

2.2 Decision-making: concepts and broad classification

Decision-making has been described by many researchers as a process by which a preferred alternative is chosen from among a set of alternatives based on input information and certain criteria (Simon, 1976; Turban *et al.*, 2004; Wang *et al.*, 2004). Other researchers suggest that decision-making is the process of sufficiently reducing uncertainty and doubt about alternatives to allow a reasonable choice to be made among them (Harris, 1998). The latter description indicates that one of the major challenges of decision-making is the uncertainty, and the goal of decision-making is to reduce this uncertainty (Kohlhammer *et al.*, 2009). Many different goals of decision-making have also been identified in the literature. For example, Bettman *et al.* (1998) organise these goals under several categories, including minimising the cognitive effort required to make the decision, minimising the experience of negative emotion when making the decision, and maximising the ease of justifying the decision. Nobre *et al.* (1999) state that the ultimate goal of decision-making is not only to choose the most preferred alternative (a choice problem) but also to obtain an order of preferences of the available alternatives (a ranking problem).

Previous research has classified the decision-making problems into three categories depending on the degree of uncertainty in the information available (French, 1986; Luce & Raiffa, 1957; Weber & Johnson, 2009). These are: 1) decision-making under certainty; 2) decision-making under risk; and 3) decision-making under uncertainty, as illustrated in Figure 2.1. Each of these categories has its own characteristics, as will be briefly explained in the following sections.

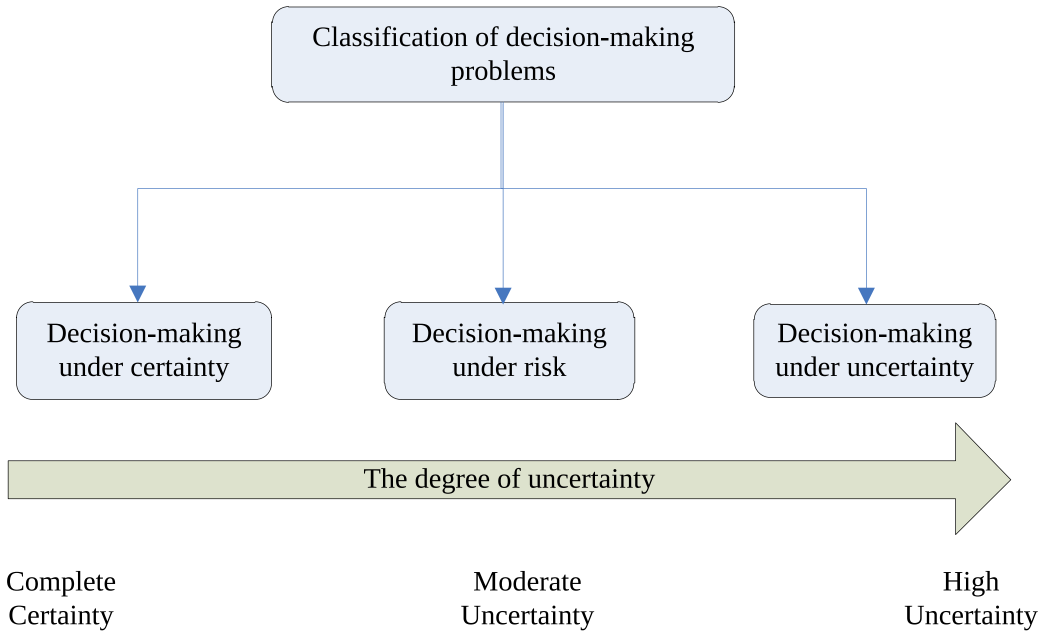


Figure 2.1: Classification of decision-making problems based on the degree of uncertainty associated with the information available to the decision-maker

2.2.1 Decision-making under certainty

Decision-making under certainty means that all information upon which decisions are based is completely available and all variables and their values are known with certainty. In the situation of certainty, the decisions are often called deterministic or riskless; i.e. for each alternative solution only one outcome is possible, and the probability of occurrence of that outcome is equal to one (Conchar *et al.*, 2004). Once alternative solutions and their associated outcomes have been identified, making the decision is relatively easy. The decision-maker simply chooses the alternative with the "best" outcome. Few decisions, however, are made under conditions of certainty. The inherent uncertainty in most decision-making problems would make such situations rare.

2.2.2 Decision-making under risk

A more common situation is decision-making under risk. This is also known as a probabilistic or stochastic decision-making situation. Decision-making under risk means that there is uncertainty associated with the information available to the decision-maker, but this uncertainty can be modelled (Kerzner, 2003; Koontz & Weihrich, 2006; Luce & Raiffa, 1957). In the situation of risk, each alternative can lead to one of many possible outcomes and the probability of these outcomes is either known or can be estimated from the input data. This implies that there is no single alternative that dominates all other alternatives in all situations. In other words, an alternative may dominate all other alternatives in particular situations, but under other situations, it could be a bad choice as it may result in an undesirable outcome.

2.2.3 Decision-making under uncertainty

As with decision-making under risk, in decision-making under uncertainty, each alternative can lead to one of many possible outcomes. However, the probability of occurrence of these outcomes is completely unknown (Kerzner, 2003; Koontz & Weihrich, 2006; Luce & Raiffa, 1957). Decision-making under uncertainty is usually handled by transforming it into decision-making under risk (Luce & Raiffa, 1957; Weber & Johnson, 2009; Webster, 2003). The decision-maker can use his or her personal knowledge, intuition, and experience to assign subjective probabilities to outcomes. Most suggestions for handling uncertainty are designed to supply the unknown probabilities of outcomes. Some suggestions are: assignment of equal probabilities, minimisation of regret, and application of game theory such as maximin and minimax rules (French, 1986; Kerzner, 2003; Koontz & Weihrich, 2006; Luce & Raiffa, 1957). For further discussion of these rules, refer to Section 2.4.2

In practice, very few decisions can be made under total certainty. Most decision-makers operate in a world which is somewhat uncertain and thus each decision alternative involves a certain amount of risk (Harris, 1998; Koontz & Weihrich, 2006). Risk is present because there is a chance that the decision made can lead to an undesirable rather than a desirable outcome. In decision-making under certainty, a “good” decision is judged by the outcomes alone. In contrast, in decision-making under uncertainty and risk, the decision-maker is concerned not only with the possible outcomes but also with the degree of uncertainty and risk each alternative entails.

2.3 Uncertainty and risk in decision-making

Since uncertainty and risk are inherent in most decision-making processes, they have been studied extensively in the literature (e.g., Bedford & Cooke, 2001; Clemen & Reilly, 2001; Simon, 1976; Slovic *et al.*, 2004; Tversky & Kahneman, 1974; Tziralis *et al.*, 2009; Walker *et al.*, 2003; Xu & Tung, 2008; Xu *et al.*, 2009). Although most studies are domain dependent, they discuss various generic aspects related to uncertainty and risk associated with decision-making. This includes how they are conceptualised, quantified, represented, integrated into the decision-making process, and communicated to decision-makers.

This section provides an overview of various aspects of uncertainty and risk in decision-making. However, this discussion will remain fairly general, as the uncertainty and risk depend largely on the nature and context of the decision-making problem. For example, in a financial decision problem, the uncertainty is associated with financial parameters (e.g. the discount rate) and the risk in this situation means the probability of losing money. In contrast, in a water management problem, the uncertainty is associated with environmental parameters (e.g. the water level) and the risk in this situation may refer to the probability of a high flood. For more comprehensive reviews, readers are referred to other studies (e.g. Clemen & Reilly, 2001; Walker *et al.*, 2003).

2.3.1 Uncertainty in decision-making

Many studies in the literature have provided useful insights into the influence of uncertainty on decision-making (e.g., Pang, 2001; Simon, 1995; Tversky & Kahneman, 1974; Vlek & Stallen, 1980; Xu & Tung, 2008). What becomes evident in their work is that the presence of uncertainty usually adds complexity and confusion to the task of decision-making which is already complicated. One example of such confusion occurs in comparing or ranking multiple alternatives, each of which may have multiple outcomes (Xu & Tung, 2008). Uncertainty implies that we might make a non-optimal choice because we may expect one outcome but something quite different might actually occur (Robinson & Thomson, 2000). Nevertheless, it is widely recognised that the explicit incorporation of uncertainty and its effects into the decision-making process would result in a better informed decision-making (Bekker et al., 1999).

Uncertainty conceptualisation

There is an extensive literature on the concept of uncertainty presented by many researchers (e.g., Ascough Ii *et al.*, 2008; Haimes, 2009; MacMillan, 2000; Walker *et al.*, 2003). However, despite the collective effort put into the conceptualisation of uncertainty, there is a lack of agreement on the definition of uncertainty. This lack of agreement is caused by overlapping ideas expressed using different terminology and viewpoints (Haimes, 2009). Walker *et al.* (2003), assert that: *"within the different fields of decision support (policy analysis, integrated assessment, environmental and human risk assessment, environmental impact assessment, engineering risk analysis, cost–benefit analysis, etc.), there is neither a commonly shared terminology nor agreement on a generic typology of uncertainties."*

Many different definitions of uncertainty have been proposed in the literature on decision-making. For example, uncertainty has been broadly defined to include concepts such as error, validity, variability, data quality, inaccuracy/imprecision, and missing data (Pang, 2001). In the domain of decision support, Walker *et al.* (2003) provide a general definition of uncertainty as being *"any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system."* Haimes (2009) defines uncertainty as *"the inability to determine the true state of affairs of a system."* Both Walker *et al.* (2003) and Haimes (2009) distinguish between uncertainty due to incomplete knowledge and uncertainty due to stochastic variability inherent in the system under consideration.

Source of uncertainty

Decision-making processes are usually affected by uncertainty arising from different sources. This uncertainty can be classified in many different ways (Ascough Ii *et al.*, 2008; Bedford & Cooke, 2001; Haimes, 2009; Maier *et al.*, 2008; O'Riordan, 1992; Simon, 1995; Walker *et al.*, 2003). A distinction can be made between “input uncertainty”, “model uncertainty”, and “model’s output uncertainty”. The input uncertainty refers to the uncertainty associated with the input variables and parameters used to provide values for a decision model or criteria. It can be caused by incomplete knowledge of the true value of a parameter or stochastic variability (Walker *et al.*, 2003). The model uncertainty is generally used to describe the uncertainty associated with the inability of the developed model to fully represent the system it attempts to model. This kind of uncertainty results from the fact that the models are ultimately only simplifications that approximate reality (French, 2003; Haimes, 2009). However, the model uncertainty is usually difficult to quantify and can also be regarded as inherent in any model. The output uncertainty refers to the cumulative uncertainty caused by the propagation of input uncertainties through the model used in decision-making (Ascough Ii *et al.*, 2008).

Uncertainty representation

Uncertainty representation consists of deriving a mathematical model to describe the uncertainty associated with the data (Correa *et al.*, 2009). Numerous techniques have been developed to quantify, represent and model the amount and nature of uncertainty. Pang (2001) argues that a large class of uncertainties can be numerically represented by *scalars*, *pairs*, *n-tuples*, or *distributions*. *Scalars* (e.g.,$10 \pm 10\%$) are often used to quantify uncertainty concepts such as confidence levels, errors or differences, likelihood, etc. *Pairs* of scalar values on the other hand are more typical of intervals or ranges (e.g., minimum-maximum ranges). *N-tuples* are usually used to represent the likelihood for a set of states or values of membership functions (e.g., fuzzy sets) (Djurcilov *et al.*, 2002). *Distributions* (e.g., uniform or normal distributions) can represent the uncertainty in the data in situations where sufficient sampling is available.

A number of alternative models and techniques also exist and are largely used in decision-making to represent and model the amount and nature of uncertainty. These include Bayesian statistics, Dempster-Shafer theory, probability distributions, belief functions, fuzzy sets, and arithmetic interval methods (Halpern, 2003). Deciding on the appropriate method for modelling the uncertainty is directly linked to the nature and availability of the data. Detailed coverage of mathematical models is beyond the scope of this thesis. For further details readers are directed to other studies (e.g. Streit, 2008).

Propagation of uncertainty through models and criteria

There are a number of techniques for propagating uncertainty through models used in decision-making. The most commonly used technique is Monte Carlo simulation (Saltelli *et al.*, 2000; Streit, 2008). In Monte Carlo simulation, the input variables are assigned probability distributions, commonly uniform or normal distributions. A random value is then drawn for each input variable or parameter according to the assigned distributions, and the calculated outcomes can then be used to characterise the range over which the outcomes can vary. Another commonly used technique for uncertainty propagation is Latin Hypercube sampling (Isukapalli & Georgopoulos, 1999; Saltelli *et al.*, 2000). In this method, the range of possible values for each of the uncertain input variables is partitioned into ordered segments of equal probability. Then only one value is drawn for each variable from each of its possible segments. For more details about these methods and others, the reader is referred to (Isukapalli & Georgopoulos, 1999; Saltelli *et al.*, 2000).

2.3.2 Risk in decision-making

Risk has long been recognised as a central issue in decision-making (Clemen & Reilly, 2001; MacMillan, 2000; Morgan & Henrion, 1990; Xu & Tung, 2008; Xu *et al.*, 2009). Conventionally, risk is conceptualised as the probability of occurrence of an outcome that would have a negative effect on a goal (Better *et al.*, 2008). Other conceptualisations view the risk as a combined function, often multiplicative, of the probability or frequency of encountering an undesirable outcome and the extent to which this outcome affects the goal (Clemen & Reilly, 2001; Helm, 1996; Kerzner, 2003; Smith, 1996; Xu & Tung, 2008). These formal conceptualisations indicate that the risk increases with increases in the probability of occurrence of an undesirable outcome and with increases in its consequences. However, this argument is largely dependent on how people assess probabilities and what they perceive as undesirable and harmful consequences (Bostrom *et al.*, 2008).

Modern theories in judgment and decision-making make a distinction between two fundamental ways in which human beings conceptualise and comprehend risk. These are the objective measures of risk, usually represented in numerical and statistical terms (e.g., $Risk = probability \times consequence$), and the perceived measures of risk, which is often called "subjective risk" or "risk perception" (Bostrom *et al.*, 2008; Maule, 2004; Slovic *et al.*, 2004). The formal conceptualisations of risk usually provide the basis for formal risk assessments. They are commonly used by professionals (e.g. risk experts), but are often interpreted differently by lay people, leading to rather different assessments than those derived by experts (Maule, 2004).

The literature on risk perception and decision-making has identified a number of deviations in how people perceive and interpret statistical based risk information. For example, people often overestimate the risk associated with low probability/high consequence events, and underestimate that associated with high probability/low consequence events (Slovic *et al.*, 2004). This bias in estimating the risk has been previously reported in the graphics perception literature, indicating that people are poor at estimating "objective risk" and have difficulty reasoning on the basis of the low-probability risks (Fisher, 1991; Halpern *et al.*, 1989; Stone *et al.*, 2003; Young & Oppenheimer, 2006). This type of argument is in keeping with prospect theory (Kahneman & Tversky, 1979), which suggests that small probabilities are often overweighted.

Research has also demonstrated that people often use information about the severity of the consequences to form their impression about the risk, rather than probability information, when they wish to act upon risk (e.g., Halpern *et al.*, 1989; Sjoberg, 2001; Stone *et al.*, 2003; Young & Oppenheimer, 2006). In line with these studies, Huber (2007) suggests that in realistic decision situations, probability information is not always used by people making decisions involving risk, even if it is explicitly displayed. Similarly, Tyszka & Zaleskiewicz (2006) suggest that not only laypeople but also experts do not so much care about probability in risky choices. In addition, many studies have shown that, when judging risk and uncertainty, people rarely process information in accordance with rational choice models, such as Expected Utility Theory (EU) (e.g., Bekker *et al.*, 1999; Tversky & Kahneman, 1974). Rather, due to their limited information-processing capacity, or bounded rationality (Simon, 1976), they often resort to simplistic modes of thinking (heuristics) (Simon, 1976; Slovic *et al.*, 2004; Tversky & Kahneman, 1974). However, the use of such heuristics can lead to bias in estimating the risk, and in so doing inhibit informed decision-making (Bekker *et al.*, 1999; Maule, 2004).

Although people have difficulty understanding probability information, quantitative risk conceptualisations and formal risk analysis remains the backbone of the standard and rational decision-making theories (Clemen & Reilly, 2001). The research into risk perception suggests that in order to "correctly" recognise and interpret a risk, people need probability information (Lion *et al.*, 2002), and the decision-making process can be improved by providing people with quantitative information concerning outcomes and probabilities, even if they do not ask for it.

Probabilistic risk analysis

Risk analysis is a difficult yet key aspect of rational decision-making (Clemen & Reilly, 2001). Probabilistic risk analysis is a method by which the uncertainty encompassing the decision variables in a decision problem are described using probability distributions and processed in order to estimate their impact on the risk and outcomes (MacMillan, 2000). During the analysis process, successive scenarios are built up using values generated from the uncertain variables which are allowed to vary within the assigned distributions. The output of a risk analysis is not a single value, but a probability distribution of all expected results. The results are then collected and analysed statistically so as to arrive at a probability distribution of the potential outcomes and to estimate the range of risk values (i.e. probabilities of encountering undesirable outcomes). The decision-maker is then provided with a complete risk-outcome profile for each decision alternative to base his or her decision on (MacMillan, 2000).

The use of probabilistic risk analysis in decision-making has a number of advantages. Firstly, probabilistic risk analysis gives the decision-maker a broad picture of the decision problem. It allows the decision-maker to describe the risk and uncertainty as a range and distribution of possible values, rather than a single discrete average or most likely value. For this purpose, a risk analysis can adopt Monte Carlo or Latin Hypercube simulations to generate a probability distribution of possible outcomes (refer to Section 2.3.1). Secondly, performing risk analysis in the form of sensitivity analysis allows the analyst (or decision-maker) to identify those variables that have the most significant effect on the resulting values of outcome (Biezma & Cristóbal, 2006; Tziralis *et al.*, 2009). However, implementing probabilistic risk analyses has limitations and presents a number of challenges. Among these is the large number of required model evaluations (MacMillan, 2000).

2.4 Approaches to decision-making under uncertainty and risk

Several approaches to decision-making under uncertainty and risk have been developed over the years. These approaches are classified in the literature in many different ways. For example, many studies have classified them into: normative, descriptive and prescriptive (Bell *et al.*, 1988; Edwards & Fasolo, 2001; French, 1988; Johnson & Busemeyer, 2010; Simon, 1976). The normative approach (or decision analysis) aims to describe how people should make decisions. The descriptive approach (or behavioural decision theory) aims to describe how people do actually make decisions. The prescriptive approach is a balance between normative and descriptive approaches, and it aims to answer the question of how people could be assisted by decision aids to make better decisions.

Other studies classify decision making approaches into two categories (e.g., Kobus *et al.*, 2001). On one hand, there are approaches of naturalistic (or 'intuitive') decision-making which rely on the notion of "situation assessment". In intuitive decision-making, decision makers apply their intuition to select among courses of action without explaining (or being able to explain) their reasoning or rationale (Nutt, 1998; Zhu & Chen, 2008). They identify preferred solutions based only on their previous experience, domain knowledge, and awareness of the situation. On the other hand, there are the analytical or computational decision-making approaches that describe the strategies available to decision makers when their task involves selecting one course of action (or option) from several possible ones (Clemen & Reilly, 2001; Howard, 1988). Zhu & Chen (2008) identify the analytical approach to decision-making as a computational approach applied to well-structured decision-making tasks,usually involving mathematical models. These models provide the decision-maker with a quantitative assessment of the decision problem and available alternatives to base his or her decision on.

2.4.1 The process of decision-making

Decision-making is usually described as a systematic process consisting of a sequence of steps. Several descriptions of the decision-making process have been developed by many researchers over the years (e.g., Au & Au, 1992; Clemen & Reilly, 2001; Simon, 1976; Turban *et al.*, 2001). Reviewing these descriptions shows that they consist of very similar elements, despite the apparent difference among them in terms of number and order of their steps.

In his seminal work, Simon (1976) describes the process of decision-making as comprising four steps: *intelligence*, *design*, *choice*, and *implementation*. Figure 2.2 illustrates this four-step process, indicating which tasks are included in each step and feedback loops between steps. Note that there is a continuous flow of information from intelligence to design to choice (bold lines), but at any step there may be a return to a previous step (broken lines).

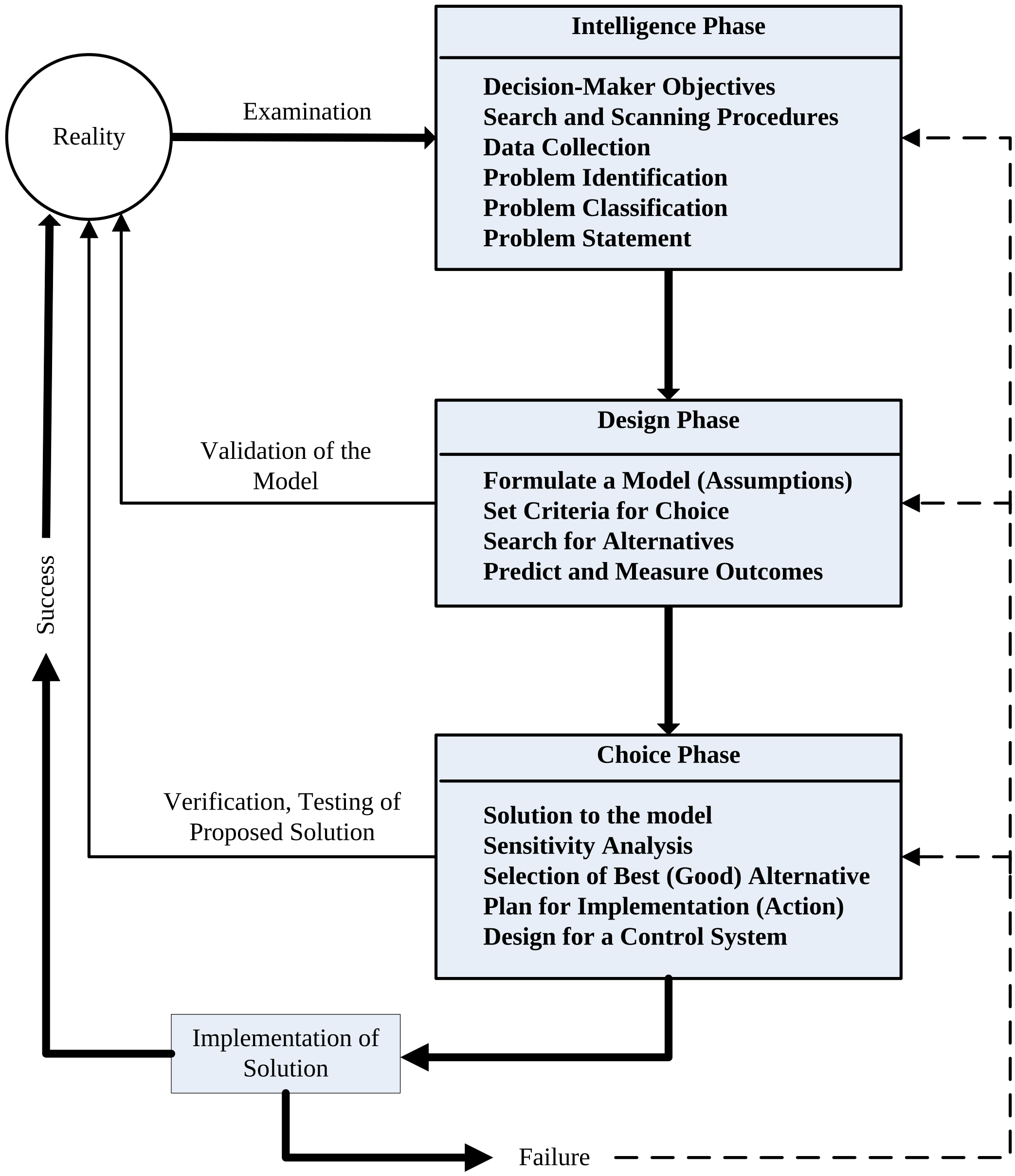


Figure 2.2: Simon's four-step decision-making process (adapted from Turban *et al.*, 2001).

The decision-making process proposed by Simon (1976) starts with the *intelligence* phase, in which the decision-maker identifies the situation calling for a decision. This step encompasses collection, classification, processing, and presentation of data pertaining to the decision problem. During the *design* step, the data collected during the *intelligence* step are now used to construct a model to simplify and predict possible outcomes for each alternative. In addition, the decision-maker outlines alternative solutions and sets criteria for evaluating the proposed alternative solutions. During this step, the model and alternatives can also be validated for feasibility using test data. The *choice* step involves selecting one of the alternatives according to the objectives of the decision-maker. However, before doing so, the decision-maker carries out a sensitivity analysis to study the effects of a change in one or more of the input variables on the inferred model outputs. Once the chosen alternative seems to be feasible and robust to changes in the input assumptions, the decision-maker enters the last step- *implementation*. Any failure in the implementation due to any factor leads to a return to the previous steps.

In comparison, Clemen & Reilly (2001), describe decision-making as a seven-step process as shown in Figure 2.3. While these steps are largely similar to those given by Simon (1976), a major difference lies in the fact that Clemen & Reilly (2001) recommend conducting sensitivity analysis after choosing the best alternative rather than conducting it before choosing the best alternative.

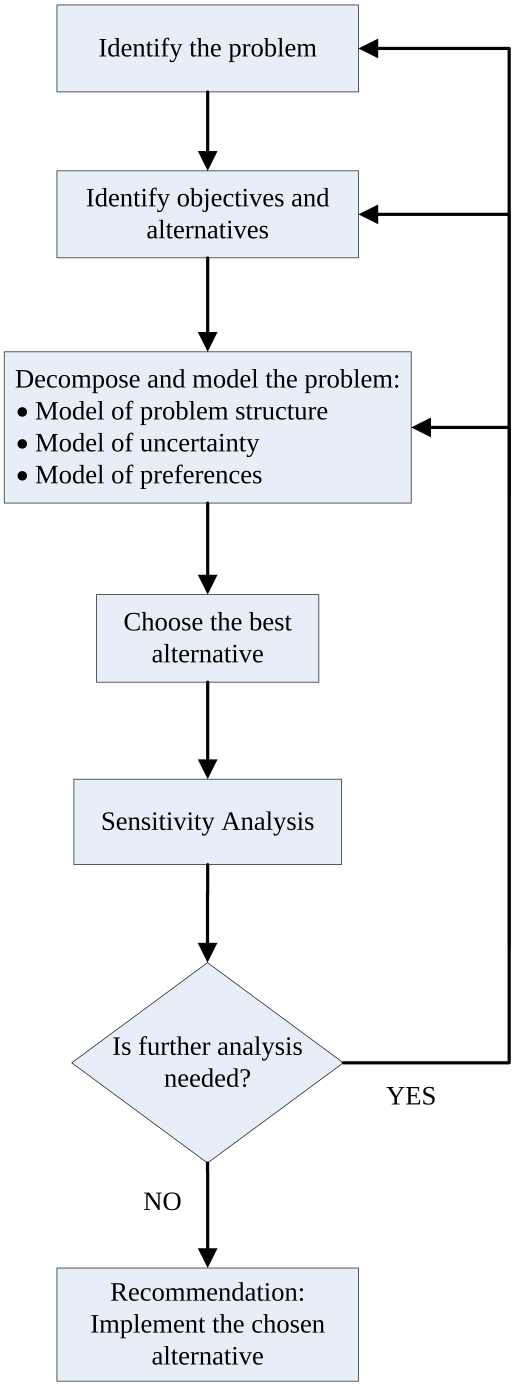


Figure 2.3: Decision Making Process (adapted from Clemen & Reilly, 2001)

The first two steps of the decision-making process proposed by Clemen & Reilly (2001) involve identification of the decision problem, objectives and alternative solutions. At this step, the decision-maker identifies the decision situation and understands his or her objectives in that situation. For example, is the objective to minimise cost, risks or maximise profit? What is meant by risk? Is it monetary loss or potentially damaging conditions for health or the environment? During these steps, the decision-maker also indicates how outcomes must be measured and what kinds of uncertainties should be considered in the analysis. After identifying the objectives and alternative solutions, the next step involves decomposition of the decision problem to understand its structure and measure uncertainty and values. This step involves the use of mathematical models that provide decision-makers with quantitative assessments of the decision problem and alternatives available. Such assessments include identification and quantification of the uncertainty and risk associated with the decision problem, as well as identification of the best alternative. After choosing the “best” alternative, sensitivity analysis is carried out to investigate how uncertainty in the input variables and criteria weights (preferences) affects the chosen alternative. If the chosen alternative is not robust to the uncertainties in the input variables, the decision-maker may determine whether further analysis is needed. This can result in either reconsidering the whole decision problem or making changes to the model structure or entering the implementation step. The arrows in Figure 2.3 show that the decision analysis process is an iterative one, indicating that the decision-maker may go through several iterations before the most preferred alternative is found.

MacMillan (2000) reviewed a number of proposed decision-making processes under uncertainty and risk (French, 1989; Goodwin & Wright, 1991; Lamb *et al.*, 1999; Morgan & Henrion, 1990; Newendorp, 1996; Thomas & Samson, 1986). Based on this review, MacMillan outlines the decision-making process as consisting of a series of steps, as follows:

1. Define possible outcomes that could occur for each of the available decision choices, or alternatives.
2. Evaluate the profit or loss (or any other measure of value or worth) for each outcome.
3. Determine or estimate the probability of occurrence of each possible outcome.
4. Compute a weighted average profit for each decision choice. This weighted-average profit is called the expected value of the decision alternative, and is often the comparative criterion used to accept or reject the alternative. The decision rule that can be applied is to choose the decision alternative with highest expected value.

Tziralis *et al.* (2009) propose a process of decision-making to help in evaluating and deciding whether to proceed or not in each of the available alternatives. The approach comprises the following steps:

1. *Select* an evaluation criterion, e.g. the Net Present Value (NPV) model
2. *Define variables* of possible alternatives according to the selected criterion
3. Apply an *appraisal* technique
4. Perform *risk analysis* in the form of *sensitivity analysis* in order to assess the volatility of the selected criterion due to changes in the variables on which it depends, and finally
5. *Decide* to proceed or not with the alternative under investigation, on the basis of the established criterion.

Modelling and sensitivity analysis

It is clear from the descriptions of the decision-making process discussed above that the steps of modelling the decision problem and performing sensitivity analysis are at the heart of the decision-making process.

The decision model is a formal, simplified representation of the decision elements (Turban *et al.*, 2001). It transforms input variables, which are set by the decision-maker, into numerical or qualitative assessments (Power, 2002). According to Clemen & Reilly (2001), the key advantages of using models from a decision-making perspective are that: 1) they can facilitate the analysis of the decision problem, which can then indicate a “preferred” alternative; 2) they can lead to a better understanding of the decision problem and relationships between its elements; and 3) they allow the decision-maker to gain insights that may not be apparent on the surface.

Models can vary significantly in complexity and can serve a variety of purposes. For example, financial managers use Net Present Value (NPV) and Internal Rate of Return (IRR) for analysing investment alternatives (Dayananda *et al.*, 2002; Jovanovic, 1999). In another decision context such as water management, decision-makers use more complex models to rank multiple water management options or compare the frequency and extent of various flooding events (Hyde *et al.*, 2005; Xu & Tung, 2008; Xu *et al.*, 2009). In practice, the decision-maker can never be certain of the values of the input variables or parameters used in the model and there may also be errors or approximations in the model itself (Jovanovic, 1999). Therefore, the results provided by the model should not directly influence the implemented decision; rather they should be further analysed. For this reason, descriptions of the decision-making process include a sensitivity analysis step.

Sensitivity analysis simply seeks to learn how the output of a model changes with variations in the inputs (French, 2003; Saltelli *et al.*, 2000). It is defined as the study of how the variation in the output of a model can be apportioned, qualitatively or quantitatively, among model inputs (Saltelli, 2002). If a small change in the value of an input variable results in a relatively large change in the output, the output is said to be sensitive to that variable.

Broadly, there are two classes of sensitivity analysis: local and global (Saltelli *et al.*, 2000). Local sensitivity analysis looks at the local impact of each input variable on the model's output. This is usually carried out by individually varying only one of the model inputs at a time over a small interval around a nominal value, while keeping all other inputs at their nominal or base-case values (Daradkeh *et al.*, 2008; Frey & Patil, 2002). The main drawback of local sensitivity analysis is that it does not take into account all possible scenarios because it relies on a small change of one variable at a time, and the change is not taken over the entire range of values of the other input variables. Therefore, it ignores the influence of interactions between input variables that might have a significant effect on the optimal alternative that is expressed by the values of the output variable. On the other hand, global sensitivity analysis methods allocate the output variability to the variability of the inputs taking into account all the variation ranges of the inputs and interactions among them (Daradkeh *et al.*, 2008; Frey & Patil, 2002). Global sensitivity analysis methods must have the following two properties: (1) the sensitivity is measured over the entire range of each input variable, and (2) all the input variables are varied at the same time (Saltelli, 2002).

Many researchers have emphasised the role of sensitivity analysis in decision-making (e.g., Clemen & Reilly, 2001; Daradkeh *et al.*, 2010; French, 1986; Triantaphyllou, 2000; Turban *et al.*, 2001). Clemen & Reilly (2001) recommend that after choosing the "best" alternative, sensitivity analysis should be carried out to investigate how uncertainty in the input variables and criteria weights (preferences) affects the values of the decision criteria. It is also carried out to investigate the relationship between changes in the criteria weights and the subsequent alteration that may occur in the ranking of alternatives (Hyde *et al.*, 2005). Such an analysis answers “what if” questions; e.g., *“If we make a slight change in one or more aspects of the model, does the optimal decision change?”* (Clemen & Reilly, 2001).

Pannell (1997) identifies a number of possible uses of sensitivity analysis in decision making. Based on his discussion, sensitivity analysis should help in:

- Testing the robustness of an optimal solution,
- Identifying critical values, thresholds or break-even values where the optimal strategy changes,
- Identifying sensitive or important variables,
- Investigating sub-optimal solutions,
- Developing flexible recommendations which depend on circumstances,
- Comparing the values of simple and complex decision strategies, and
- Assessing the "riskiness" of a strategy or scenario.

According to Turban *et al.* (2001), sensitivity analysis allows the decision-maker to judge in a formal and structural manner:

- The influence of changes in input data – decision and uncontrollable variables – on the proposed solution that is expressed by the values of output variables;
- The effects of interactions between variables on the proposed decision;
- The minimal changes of preferential parameters that are required to obtain (un)desirable results; and
- The robustness of both the decision model and the suggested decision in dynamically changing conditions.

French (2003) asserts that fundamentally, the many different purposes for which sensitivity analysis may be used are concerned with building understanding about the influence of input variables and relations between them on the derived results. The understanding that could be gained through sensitivity analysis is a key prerequisite for making informed and justifiable decisions. This assertion is in line with Tufte (1997) who asserts that “*Assessments of change, dynamics, and cause and effect are at the heart of thinking and explanation. To understand is to know what cause provokes what effect, by what means, at what rate.*”

2.4.2 Rules for decision-making under uncertainty and risk

Several rules have been proposed to resolve the problem of decision-making under uncertainty and risk. Table 2.1 outlines some of the most commonly used rules. The application of these rules depends to a large extent on the decision-maker's attitude towards risk. This attitude is categorised in the literature into the following three types (Liu, 2004; Raiffa, 1968; Smith & Slenning, 2000):

- *Risk averse or pessimistic attitude*: in this case, the decision-maker prefers a low-risk/low-return alternative to a high-risk/high-return alternative. The "risk averter" will most likely choose alternatives with relatively modest but rather safe returns.
- *Risk neutral*: in this case, the decision-maker tends to choose an alternative that maximises the expected outcomes of the corresponding utility, regardless of the distribution of the outcomes.
- *Risk prone or optimistic attitude*: in this case, the decision-maker prefers a high-risk/high-return alternative to a low-risk/low-return alternative. The "risk lover" will most likely choose alternatives with relatively high return (gain), showing less concern for the risk involved.

Based on the decision-maker's attitudes towards risk, the rules of decision-making can be classified into: *optimistic*, *neutral*, and *pessimistic* (Liu, 2004; Smith & Slenning, 2000) as summarised in Table 2.1.

Table 2.1: Summary of decision rules under conditions of uncertainty and risk.

Classification	Decision rule	Description of the rule
Optimistic	Maximax	Select the alternative which results in the maximum of alternative maximum outcomes.
	Minimin	Select the alternative which results in the minimum of alternative minimum outcomes.
Neutral	Hurwicz criterion (Hurwicz, 1951)	Select the alternative that has the largest weighted average of its maximum and minimum outcomes.
	Laplace insufficient reason criterion (Laplace, 1825)	Calculate the average of each alternative by assuming that the outcomes are equally likely to occur, and select the alternative with largest average.
	Expected value (EV)	Select alternative that maximises the expected value (i.e. actual outcome)
Pessimistic	Maximin criterion (Wald, 1950)	Select the alternative that maximises the minimum outcome
	Minimax	Select the alternative that results in the minimum of maximum outcomes (in this case the outcomes refer to costs)
	Minimax regret strategy (Savage, 1951)	Select alternative which results in the minimum of maximum regret
ALL[1]	Expected Utility (EU)	Select alternative which maximises the expected utility of the outcomes
	Subjective Expected Utility (SEU)	Select alternative which maximises the subjective expected utility of outcomes

Maximax and minimin

Both maximax and minimin are optimistic rules (Liu, 2004; Raiffa, 1968). The maximax rule suggests that the decision-maker examines the maximum outcomes of

[1] Allow for incorporating the attitude of decision-makers towards risk into decisions.

alternatives and chooses the alternative whose outcome is the best. This rule appeals to the adventurer decision-makers who are attracted by high outcomes. The main drawback of the maximax strategy is that it ignores the possible losses from the selected alternative (Smith & Slenning, 2000). The minimin rule is also based on an extremely optimistic (or non-conservative) view of the outcomes associated with the decision alternatives (Smith & Slenning, 2000). The minimin rule is used in the case of costs rather than profits. The decision-maker first selects the minimum cost that is related to each alternative and then chooses the alternative that minimises the minimum cost (Raiffa, 1968).

Maximin and minimax

On the other hand, both of the maximin and minimax are pessimistic rules usually followed by “risk averse” decision-makers (Smith & Slenning, 2000). The maximin rule suggests that the decision-maker examines the minimum possible outcome associated with each alternative. Then the decision alternative that yields the maximum value of the minimum outcomes (i.e. the alternative with the smallest possible loss) is selected. The maximin rule appeals to the cautious or pessimistic decision maker who directs his or her attention to the worst outcome and makes it as desirable as possible. In contrast, the minimax rule is applied to costs data. The decision-maker examines the maximum cost associated with each alternative, and then the alternative with minimum of maximum costs is selected. The application of the maximin or minimax rules may reduce the opportunities for available profit, which normally only result from a willingness to take some risks (Beenhakker, 1996).

Another variant of minimax is the minimax regret rule, sometimes called the Savage rule (Savage, 1951). It aims to minimise the regret that the decision-maker feels following a wrong decision (French, 1988). The minimax regret rule is based on the assumption that a decision-maker wants to avoid any regret or at least to minimise the maximum regret that represents the possible loss due to not selecting the best alternative. The regret is defined as the difference between the maximum outcome that could have been received and the outcome that was actually obtained from the alternative selected (Kahraman & Tolga, 1998).

Hurwicz rule

In order to overcome the disadvantages of pessimism of maximin and optimism of maximax rules, Hurwicz (1951) introduced the concept of coefficient of optimism (or pessimism). The Hurwicz rule takes the best and worst outcomes of each alternative and assigns weights according to a coefficient of optimism α, where $0 \leq \alpha \leq 1$, that describes the degree of optimism of the decision-maker (note: $1 - \alpha$ represents the degree of pessimism). The alternative with the largest sum of these weighted outcomes is then selected according to $Sum = \alpha \times maximum\ outcome + (1 - \alpha) \times minimum\ outcome$ for each alternative. In case of extreme optimism$(\alpha = 1)$, the Hurwicz rule becomes the maximax rule, whereas the case of extreme pessimism$(\alpha = 0)$ gives the minimax rule. The Hurwicz rule can be criticised due to the difficulty of assigning a particular value to α (Huynh *et al.*, 2009).

Laplace rule

The Laplace insufficient reason rule (Laplace, 1825) is an attempt to transform decision-making under uncertainty into decision-making under risk (Raiffa, 1968). This rule, also called the equal likelihood rule, postulates that if no information is available about the probabilities of the various outcomes, it is reasonable to assume that they are equally likely (Luce & Raiffa, 1957). Therefore, if there are n outcomes, the probability of each is $1/n$. This rule also suggests that the decision-maker calculates the expected outcome for each alternative and then selects the alternative associated with the largest expected outcome (Raiffa, 1968). In this case, the expected outcome is equivalent to the mean value; hence the alternative with best mean value is selected. The use of expected values (EV) distinguishes this rule from the rules that only use extreme outcomes. This characteristic makes the approach similar to decision making under risk (Raiffa, 1968). It may also be possible to obtain probability estimates for each possible outcome. In this case, the expected value (EV) theory can be used to identify the best decision alternative.

Expected Value , Expected Utility, and Subjective Expected Utility rules

The three most popular rules for decision-making under uncertainty and risk are the classical Expected Value (EV), Expected Utility (EU) and Subjective Expected Utility (SEU) theories (Weber & Johnson, 2009).

EV is a strategy that simply employs all possible outcomes together with the assigned probability of each outcome to select the alternative that will produce the greatest expected value (i.e. weighted average) of the possible outcomes. Mathematically:

$$EV = \sum_i p_i \times x_i \tag{4}$$

Where p_i denotes the probability of a particular outcome x_i (Weber & Johnson, 2009).

Decision theorists have also proposed that people maximise expected utility (EU) rather than expected value (Weber & Johnson, 2009). The term “Utility” is commonly used in decision-making to refer to a subjective value, which is different from the actual value of a choice. In decision-making, the term utility refers to a numerical measure representing the satisfaction that an individual could gain from a particular outcome of a choice. For example, \$100 to a poor person is likely to have a relative value, or utility, exceeding the same \$100 to an extremely wealthy person. This is because \$100 increases a poor person’s wealth by a greater proportion than a wealthy person. As a practical matter, the utility cannot be computed directly; rather, it could be inferred by observing people’s choices and preferences. Moreover, the utility depends on differences not only among individuals but also within an individual, depending on the decision situation and context (Robinson & Thomson, 2000).

The Expected Utility rule, first formulated by Neumann & Morgenstern (1944), states that the decision-maker will select the alternative with the highest expected utility. The expected utility (EU) is the sum of the utilities of all possible outcomes of a decision alternative, weighted by their calculated probabilities; thus,

$$EU = \sum_i p_i \times U(x_i) \tag{5}$$

Where p_i denotes the calculated probability of outcome i and $U(x_i)$ denotes the utility derived from the actual outcome x_i (Weber & Johnson, 2009).

Another major rule of decision-making under uncertainty and risk is the Subjective Expected Utility (SEU) (Edwards, 1962; Fischhoff *et al.*, 1981). SEU is a rational approach in which the uncertainty and risk are incorporated into the decision model by assigning probabilities, estimated by the decision-maker, to potential outcomes. As in EU, in SEU, the worth derived from the actual outcome is expressed in utility.

However, the probabilities of these outcomes are treated as being subjective rather than objective. SEU states that when making decisions under uncertainty and risk, people choose the alternative with the highest utility, which is dependent on the potential outcomes, x_i, the utility of each outcome, $U(x_i)$, and the subjective probability of each outcome, $P(x_i)$, as described by the following equation:

$$SEU = \sum_{i=1}^{n} U(x_i)P(x_i) \tag{6}$$

In their seminal work Kahneman & Tversky (1979) criticised the SEU as a descriptive model of decision-making under risk and uncertainty. They stated that SEU fails because people do not structure problems and process information, especially probabilistic, according to the SEU. Hence, they presented an alternative for SEU, which they call *prospect theory* to describe how utilities can be affected by how information is framed or presented.

Another problem that constitutes a barrier to the adoption of rational models of decision-making such as SEU is what Simon (1976) has called *bounded rationality*. *Bounded rationality* refers to the cognitive limits experienced by decision-makers in their ability to process and interpret a large volume of complex and uncertain information in decision-making activities. To cope with the limited information processing and cognitive abilities, decision-makers often base their decisions activities on a salient subset of the available information that they perceive as being most informative to guide the decision-making process (Hilary & Menzly, 2006; Kahneman & Frederick, 2005; Simon & Houghton, 2003). Furthermore, they often employ more simplistic methods or strategies that would enable them to process information with less effort than that required from a rational decision model (Fischhoff *et al.*, 1982; Shah & Oppenheimer, 2008; Tversky & Kahneman, 1974). Such methods and strategies are often called decision *heuristics*.

Simon (1990) argued that the decision heuristics are *"methods for arriving at satisfactory solutions with modest amounts of computation."* They are typically expressed as verbal rules or flowcharts for applying discrete tasks and activities to make a decision (Johnson & Busemeyer, 2010). The use of heuristics in decision-making can be a relatively efficient way to solve decision problems. However, they can also lead to systematic and predictable errors and biases in judgments and decision-making

(Tversky & Kahneman, 1974). Many heuristics have been proposed (for a review see, for example, Shah & Oppenheimer, 2008). In particular, under uncertainty and risk, Tversky & Kahneman (1974) described three general purpose heuristics that underlie many other heuristics of decision-making. These are: *availability*, *representativeness*, and *anchoring and adjustment*.

The *availability* heuristic suggests that the decision-maker bases a decision and the subjective estimation of the probability of a potential event on the ease with which instances or occurrences of similar recent events are brought to mind. For example, one may assess the risk of heart attack among middle-aged people by recalling such occurrences among one's friends (Tversky & Kahneman, 1974). The *representativeness* heuristic suggests that the decision-maker bases a decision on the resemblance between the situation at hand and stereotypes of similar occurrences; it suggests that the subjective estimation of the probability that a potential event A (sample) belongs to a set of events B (population) by the degree to which A is similar to or resembles B. For example, the estimate of the probability that a person is a librarian is affected by the degree to which he/she is representative of, or similar to, the stereotype of a librarian. Finally, the *anchoring and adjustment* heuristic implies the availability of a starting value or initial anchor that readily comes to mind. The decision-maker then subjectively estimates the probability of a potential event by using the starting value and then adjusting it to arrive at a final decision. For example, you may judge another person's level of knowledge based on your own knowledge (the anchor) that is adjusted to arrive at a final judgment of the person's level of knowledge.

The use of heuristics in decision-making is also associated with a set of *decision biases*; i.e. predictable deviations from rationality (Arnott, 2006). For example, the use of the availability heuristic leads to biases in likelihood estimation of cases that are easily retrieved from memory or considered dramatic ones. Many other biases that are related to decision-making and estimating probabilities of events have also been identified by researchers in the domain of decision-making. Many studies have demonstrated that the decision biases may lead to misinterpretations of risk, and in so doing inhibit informed and effective decision-making (e.g., Kahneman & Frederick, 2005; Maule, 2004; Nisbett & Ross, 1980; Zacharakis & Shepherd, 2001). Moreover, they can also result in decisions being made from the context rather than the content of the information (Bekker *et al.*, 1999).

2.5 Measures of informed decision-making under uncertainty and risk

Evaluating the effectiveness of decision-making under uncertainty and risk continues to pose considerable challenges (Edwards & Fasolo, 2001). Any research into decision-making has, at its heart, the desire to improve and facilitate "better" decision-making. Many studies in the literature of decision-making have assessed better decision-making by measuring the accuracy of the decision made (e.g., Johnson & Payne, 1985; Schweizer, 1996; Speier, 2006). Indeed, an accurate or "right" decision often exists in decision-making under certainty or in theoretical situations that deal with facts or logic. Most real-world decision problems involve uncertainty and risk. Owing to the nature of decision-making under uncertainty and risk, reasoned decisions can still result in bad outcomes, due to the uncertain and stochastic nature of the decision variables/parameters. In such situations, reasoned decisions cannot be judged as right or wrong; rather, reasoned decisions are those that are informed and consistent with the decision-maker's objectives and preferences (Robinson & Thomson, 2000).

In a systematic review of informed decision-making, Bekker *et al.* (1999) have discussed the problems associated with defining "informed decision" and offer the following: "*An informed decision is one where a reasoned choice is made by a reasonable individual, using relevant information about the advantages and disadvantages of all possible courses of action, in accord with the individual's beliefs*." Green *et al.* (2004) state that a decision is said to be informed when the relevant information about the advantages and disadvantages of all the possible courses of action is evaluated in accord with the decision-maker's beliefs. Alternatively, Kohut *et al.* (2002) state that an informed choice is considered a process of decision-making, which evolves through the evaluation of information and personal values. According to these definitions, there are two dominant dimensions of informed decision-making: the decision outcomes and process of decision-making. In arriving at an informed decision the decision-maker must not only have sufficient information but also be able to process and exploit this information in a way that is consistent with his or her objectives (Robinson & Thomson, 2000).

Bekker *et al.* (1999) identify several measures of informed decision-making. These include: the consistency between the final decisions and the decision-maker's preferences, confidence of the decision-makers in making informed decisions, and the availability of relevant information to make better informed decisions. However, all of these measures focus on the outcomes after making a decision, and hence, do not reflect the multidimensional nature inherent in the definition of informed decision (Marteau *et al.*, 2001). Therefore, in addition to the measures pertaining to decision outcomes, studies evaluating the facilitation of informed decision-making should include an analysis and evaluation of the decision-making processes adopted by individuals. The decision-making process measures may include: the operations carried out by individuals to arrive at final decisions, the type of information and the way it was used in decision-making, attitudes, preferences, perception of risk, and perception of severity (Bekker *et al.*, 1999). Due to the qualitative nature of these measures, Bekker *et al.* recommend qualitative studies as they usually provide the best understanding of how decisions are made. Such studies are recommended to integrate measures of both decision outcomes and process, utilise process tracking techniques and observational methods, and assess the effect of additional information and manipulation of information (Bekker *et al.*, 1999).

2.6 Summary and discussion

This chapter has provided background information to decision-making under uncertainty and risk. A brief discussion of the main points is presented in this section, while more detailed discussion will be included in Chapter 4.

Decision-making under uncertainty and risk is usually described as a process of choosing between alternatives, each of which can lead to one of many possible outcomes. These outcomes reflect the uncertain and stochastic nature of input variables and their propagation through the model and criteria used in the decision-making process. Not all possible outcomes are equally desirable to decision-makers. Consequently, risk accompanies decisions because there is a chance that the decision made can result in an undesirable rather than a desirable outcome. From this description, there are four generic elements of the decision problem under uncertainty and risk. These are: 1) the set of alternatives from which a preferred alternative is chosen; 2) the input information and its associated uncertainty; 3) the range of possible outcomes associated with each alternative and their probabilities; and 4) the risk of obtaining desirable or undesirable outcomes each alternative entails.

Owing to the nature of decision-making under uncertainty and risk, reasoned decisions cannot be judged as right or wrong. Rather, reasoned decisions are those that are well-informed and consistent with the decision-maker's objectives and preferences. Informed decision-making under uncertainty and risk is based on three prominent considerations. Firstly, it is based on the provision of sufficient, unbiased and relevant information about the decision problem and its elements. Secondly, it is based on the ability of decision-makers to process and utilise information to arrive at decisions that are consistent with their objectives and preferences. Thirdly, it is based on the explicit consideration of uncertainty and its associated risk as an integral part of the information on which decisions are based.

One major obstacle to informed decision-making is that human decision-makers are known to have limited information processing and cognitive capabilities. Hence, even if they were provided with comprehensive information on the decision problem, they don't usually utilise it all when making a decision. Adding to this obstacle, the integration of uncertainty and risk into the decision-making process poses significant cognitive challenges. It adds complexity and confusion to the task of decision-making which is already complicated. One example of such confusion occurs when comparing or ranking multiple alternatives, each having multiple outcomes. Moreover, the integration of uncertainty and its associated risk is a highly technical subject, and usually not transparent to decision-makers who lack the necessary numerical skills.

All these problems— uncertainty, risk, and limited information-processing and cognitive capacity — will not simply disappear because of the incremental advances in the technology available to human decision-makers. The crux of the problem is that these problems are human-centric. Thus, their resolution will not occur by replacing humans in the decision-making process, but rather by supporting them with technological aids that can raise their awareness of uncertainty and its associated risk and enhance their information processing and cognitive capabilities.

CHAPTER 3
INFORMATION VISUALISATION TO SUPPORT DECISION-MAKING

3.1 Introduction

One technology that has emerged as a vital aid to judgment and informed decision-making is information visualisation (Tarantino, 2000; Ware, 2004). Over the last two decades, some theoretical frameworks that establish relationships between the two areas of information visualisation and decision-making have been proposed (e.g., Amar & Stasko, 2005; Bautista & Carenini, 2006; Yi, 2008). In addition, several InfoVis techniques have been developed to facilitate analysis and support decision-making in many different areas (e.g., Carenini & Loyd, 2004; Johnson & Shneiderman, 1991; Sauter *et al.*, 2011; Yi, 2008; Zhu *et al.*, 2007).

This chapter reviews the relevant literature on information visualisation to support decision-making. The purpose of this review is to explore the various roles information visualisation could play in the support of decision-making, particularly in the presence of uncertainty and risk. To this end, it begins by providing an overview of the impact of information visualisation technology on decision-making support in Section 3.2. Section 3.3 reviews the theoretical frameworks and InfoVis techniques that have been developed to support decision-making. Section 3.4 briefly presents the applications of information visualisation in areas related to decision-making; namely, uncertainty, risk and sensitivity analysis. This chapter ends with the summary and discussion in Section 3.5.

3.2 The impact of information visualisation on decision-making support

Information visualisation is defined by Card *et al.* (1999) as "*the use of computer-supported, interactive, visual representations of abstract data to amplify cognition*." It can amplify human cognition in six basic ways: (1) by increasing the memory and processing resources available to the users; (2) by reducing the search for information; (3) by using visual representations to enhance the detection of patterns; (4) by enabling perceptual inference operations; (5) by using perceptual attention mechanisms for monitoring; and (6) by encoding information in a manipulable medium (Card *et al.*, 1999).

Because of its ability to amplify cognition, information visualisation can enhance the ability of decision-makers to process and use information in decision-making (Dull & Tegarden, 1999). It offers a way to shift the cognitive load required to perform decision-making tasks to the human perceptual system, which provides a high-bandwidth data-channel to the human brain (Gröller, 2002). Miller (1956) reports that a human's input channel capacity can be increased when visual abilities are used. He states that different parameters in the visual channel can be exploited to increase the amount of information that the decision-maker can process (Dull & Tegarden, 1999). Consequently, with the support of visualisation, the decision-maker can solve complex decision problems that would be impossible without visual representation of their elements (Speier *et al.*, 2003; Zhu & Chen, 2008).

In addition, information visualisation provides an effective means for presenting information to decision-makers in ways that make it amenable to analysis and exploration. Zhou & Feiner (1998) group the main goals of information visualisation into two high-level intents: "*inform*," which deals with the analysis and elaboration of information, and "*enable*," which deals with information exploration. Through visual analysis and exploration of information, decision-makers can identify relevant information that may otherwise be difficult to recognise. For example, they might discover hidden relationships, which provide useful information for informed decision-making. As asserted by Bertin (1983) "*in decision-making the useful information is drawn from the overall relationships of the entire set.*" Information visualisation also allows decision-makers to quickly identify outliers (e.g. extreme possible outcomes), distributions of possible outcomes and different patterns of risk. Furthermore, information is more easily evaluated and compared when it is presented in visual forms.

Information visualisation can provide decision-makers with a better level of insight and understanding into the decision problem at hand, especially in cases in which they do not have the technical expertise to fully understand the statistical results. It can facilitate the interaction between the decision-maker and decision model by converting it from a difficult conceptual process into a simple perceptual process (Zhu *et al.*, 2007). It also can help decision-makers to experiment with "what-if" scenarios. The ability to analyse "what-if" scenarios is a key requirement for developing understanding about the implications of uncertainty, which in turn leads to making better informed and justifiable decisions (French, 2003). According to Tufte (1997) *"Assessments of change, dynamics, and cause and effect are at the heart of thinking and explanation.*"

To design effective InfoVis for decision-making support, the designer must first understand how information is processed by humans and how decisions are made in reality (Kohlhammer *et al.*, 2009). One needs to understand what types of decision problems decision-makers face, what kinds of information are available about the decision problem, how decision-makers solve and analyse their problems, and how they evaluate and identify their preferred alternatives (Zhang, 2001). A typical decision-making process usually includes the analysis of the decision situation, the formulation of models for representing the problem and alternatives, and the identification of a preferred alternative as assessed by certain criteria. Each of these steps could be augmented by visualisation in different ways. For example, evaluation of decision alternatives involves the use of both detailed and holistic information. Visualisation could be used to provide the decision-maker with a quick overview of the related information, as well as detailed information for evaluation and comparison purposes.

3.3 Frameworks and InfoVis techniques to support decision-making

In this section some of the known frameworks and InfoVis tools that have been developed to support decision-making are reviewed as baseline design guidelines.

3.3.1 Models and frameworks of InfoVis

Shneiderman (1996) introduced one of the most influential and succinct frameworks for the design of InfoVis techniques, known as the visual information-seeking mantra. This three-step mantra, "*Overview first, zoom and filter, then details-on-demand*", can be read as a design guideline summarising many of the requirements of effective information visualisation design. Although it is not designed specifically to link the two domains of information visualisation and decision-making, it can be effectively used for the design of InfoVis techniques to support decision-making. A visualisation first provides an overview of the entire dataset (e.g., all decision alternatives); displaying high level features of the data to allow the user to identify a region of interest. Then, through zooming and filtering, users can target a region of interest or remove irrelevant information from the display. Zoom and filter can be approached by methods such as: removing the context from the display, providing more detail on an important region while maintaining the context (focus + context), or highlighting a region of enlargement on the overview display and then showing detail in a new window (overview + detail) (Cockburn *et al.*, 2008). Finally, details-on-demand provides more detailed features of the data. A common means for details-on-demand is using separate display panels for the text details. Another common means is a pop-up window that appears when the user clicks on or hovers over a particular item or location in the scene.

More recently, Amar & Stasko (2005) proposed a set of knowledge precepts for design and evaluation of information visualisation to support decision-making, particularly under uncertainty. They argue that frameworks like Shneiderman's mantra typically centre on faithful correspondence of representation to data, but fail to support higher-level analytical tasks such as decision-making under uncertainty. They assert that the three main weaknesses of current information systems are: 1) the limited affordance; 2) the predetermined representations; and 3) the decline of determinism in decision-making. To address these weaknesses, they introduce the concept of "*analytic gaps*" which are the gaps between representation and analysis. To bridge these analytic gaps, they propose two categories of knowledge precepts for design and evaluation of information visualisation. The first category is the "*rationale gap*" and the second category is the "*worldview gap*."

The *rationale gap* is described as the gap between seeing a relationship and confidently understanding it in terms of making a decision. To bridge this gap, Amar and Stasko propose the following knowledge tasks:

1. *Expose uncertainty* (expose uncertainty in data measures and aggregations, and show possible effects of this uncertainty on outcomes);
2. *Concretise relationships* (clearly present what comprises the representation of a relationship, and present concrete outcomes where appropriate); and
3. *Formulate cause and effect* (clarify possible sources of causation).

On the other hand, the *worldview gap* is described as the gap between what is being shown and what actually needs to be shown to draw a conclusion for making an informed decision. To bridge this gap, they propose the following knowledge tasks:

1. *Determine domain parameters* (provide facilities for creating, acquiring and transferring knowledge or metadata about important parameters within a data set);
2. *Multivariate explanation* (provide support for discovery of useful correlative models and constraints); and
3. *Confirm hypothesis* (provide support for the formulation and verification of hypotheses).

Keim *et al.* (2006) extended Shneiderman's information-seeking mantra to bring its focus toward Visual Analytics: *"Analyze First – Show the Important – Zoom, Filter and Analyze Further – Details on Demand."* They argue that the field of decision-making constitutes a further visual analytics challenge. This is because most of the real-world decision problems are complex, opaque and often involve trade-offs between objectives. In addition, the information on which decisions are based is not absolutely exact and can change over time. Therefore, it may not be possible to create an overview of the decision problem and all data that need to be analysed without losing interesting patterns. Unlike the information seeking mantra, the visual analytics mantra comprises the application of automatic analysis methods such as statistical analysis and data mining methods before and after the interactive visual representation is used. The visual analytics mantra could be effectively applied for designing InfoVis tools to support decision-making and analysis. The decision alternatives and outcomes can be analysed first in terms of sensitivity and uncertainty, and displayed to the user. The user can then proceed and choose a subset of available alternatives by applying filtering and zooming interaction techniques. This subset can be used for further analysis and exploration. Details on uncertainty and risk associated with a particular alternative under particular scenarios can also be retrieved.

Another step towards linking information visualisation to decision-making is the Preferential choice Visualisation Integrated Task (PVIT) model proposed by Bautista & Carenini (2006). Figure 3.1 outlines the PVIT model as subtasks of three main phases of the decision-making process: *construction, inspection, and sensitivity analysis*. In the development of the PVIT model, the authors adopted a decision-making process proposed by Clemen & Reilly (2001), which is described in Section 2.4. Then, they incorporated Shneiderman's Task by the Data Type Taxonomy (TTT) (Shneiderman, 1996), Amar & Stasko's knowledge tasks (Amar & Stasko, 2005), Carenini and Loyd's basic conceptual tasks (Carenini & Loyd, 2004), and tasks from Adaptive Decision-Making and Value-Focused Thinking approach (Keeney, 1992; Payne *et al.*, 1993) into their framework. The result of their task analysis and integration is a set of 20 basic tasks organised into two dimensional spaces: decision-making phases and the relevance of the tasks to the decision-model or alternatives. The relevance dimension includes the alternatives, the model, and the model + alternatives. Based on this model, the authors provided an InfoVis tool called ValueChart+ to support decision-making that is discussed in the next section.

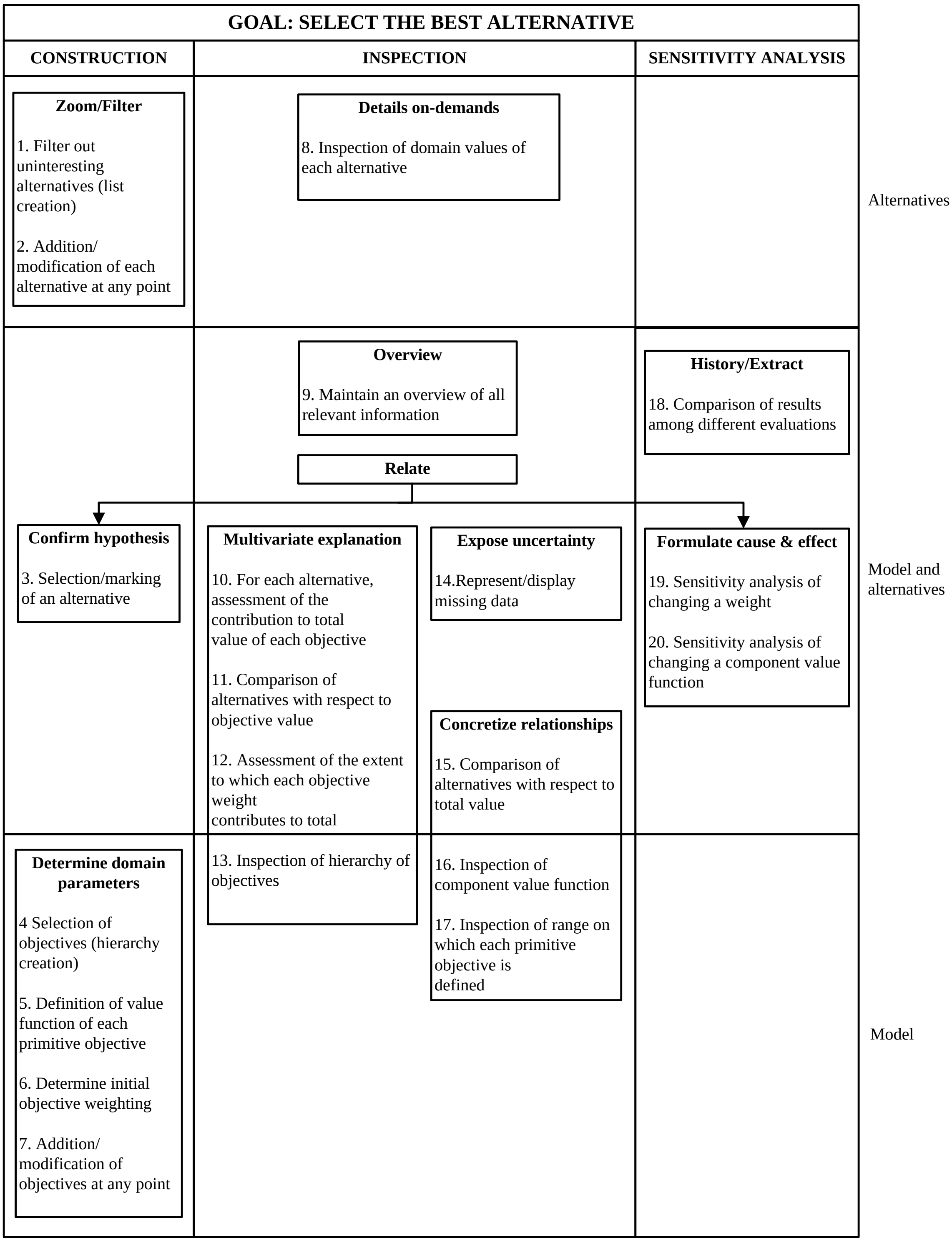


Figure 3.1: Preference choice Visualisation Integrated Task model (PVIT) (adapted from Bautista & Carenini, 2006)

More recently, Yi (2008) developed the Visualised Decision-Making (VDM) framework to link the field of information visualisation to decision-making based on Bautista & Carenini's PVIT model described above. The VDM framework uses low-level cognitive tasks to connect terminologies from the two domains of information visualisation and decision-making. The resulting list of cognitive tasks and decision rules is shown in Table 3.1. Yi integrated tasks from the PVIT model, high-level analytic tasks from Amar *et al.* (2005), and the result of his own task analysis into VDM. A set of rules for decision-making under certainty is analysed to identify the low-level cognitive tasks involved in these rules. Then, these rules are connected to information visualisation techniques through cognitive tasks. For example, one low-level cognitive task used in satisfying (SAT) and Eliminate-by-aspects (EBA) rules (Payne *et al.*, 1993) is to “Filter out uninteresting alternatives.” Filtering out uninteresting alternatives is one of the basic information visualisation techniques as well, and visualisation tools such as Attribute Explorer (Tweedie *et al.*, 1994) can support such a task.

The decision rules in the VDM framework are categorised into: compensatory and non-compensatory. In compensatory rules, a good value of one criterion compensates for a bad value of another criterion, so all criteria are considered at the same time. Conversely, non-compensatory rules could drop a choice with a bad value of a criterion, even if the choice has perfect values for the other criteria (Bettman *et al.*, 1998; Wright, 1975). The cognitive tasks in the VDM framework are grouped into one of three categories: supporting compensatory decision rules, supporting non-compensatory decision rules, and supporting both as shown in Table 3.1.

Table 3.1: The Visualised Decision-Making (VDM) Framework (adapted from Yi, 2008)

Categories of decision rules	Decision rules [4]	Low-level cognitive tasks	InfoVis techniques
Compensatory	EQW, WADD, MAU	• Selection of objectives (hierarchy creation) • Definition of value function of each primitive objective • Determine initial objective weighting • Addition/modification of objectives at any point • Inspection of hierarchy of objectives • Inspection of component value function • Inspection of range on which each primitive objective is defined • For each alternative, assessment of the contribution to total value of each objective • Assessment of the extent to which each objective weight contributes to total score • Comparison of alternatives with respect to total value • Comparison of results among different evaluations • Sensitivity analysis of changing a weight • Sensitivity analysis of changing a component value function	ValueCharts, AHP TreeMap, Dust & Magnet, Parallel Coordinates
	MCD	• Comparison of two alternatives and determine the winner	-
	VOTE	• Addition of marks for positive and negative attributes of each alternative	-

Non-compensatory	SAT, EBA	• Addition/modification of each alternative at any point • Filter out uninteresting alternatives (list creation) • Characterise distribution • Determine range	Dynamic Query Attribute Explorer Summary Statistics
	LEX	• Comparison of alternatives with respect to objective value	Colour coding, Sorting, ValueCharts, Table Lens, Dust& Magnet
	MINIMAX MAXIMIN	• Find extremum	
Both	All	• Inspection of domain values of each alternative • Selection/marking of an alternative • Maintain an overview of all relevant information • Represent/display missing data	Table, Annotation, Marking, Table Lens, Overview + Detail, Focus + Context, Zooming, Uncertainty visualisation

[4] Equal weight (EQW), Weighted additive (WADD), Multi attribute utility (MAU), Majority of confirming dimensions (MCD), Feature voting (VOTE), Satisficing (SAT), Eliminate-by-aspects (EBA), Lexicographic (LEX), Maximise Minimum (MINIMAX), and Maximise maximum (MAXIMAX) (adapted from Payne *et al.*, 1993)

3.3.2 InfoVis tools to support decision-making

In this section some known examples of InfoVis tools that have been designed and applied to support decision-making are described. In our review of the literature, we have identified the following examples of InfoVis tools: AHP TreeMap (Asahi *et al.*, 1995), ValueCharts and ValueCharts+ (Bautista & Carenini, 2006; Carenini & Loyd, 2004), Dust & Magnet (Yi *et al.*, 2005), Decision Map and Decision Table (Yi, 2008), and Decision Tree (Quinlan, 1987, 1990).

AHP TreeMap (Asahi *et al.*, 1995) is a visual interface that uses a TreeMap visualisation to support decision-making based on the Analytical Hierarchy Process (AHP) developed by Saaty (1980). AHP is a multi-criteria decision-making approach that decomposes the decision problem into a hierarchal structure with three main levels: the goal, the criteria of evaluation, and the alternatives available. Figure 3.2 shows an example of a TreeMap generated for analysing and solving a decision-making problem of “software package selection” based on AHP. The problem space in this example consists of two alternatives, “soft B”, and “soft X.” The major criteria used to evaluate these alternatives are: service, specification, price and usability. These criteria are subdivided into a number of sub-criteria; for example, the service criterion is divided further into maintenance, instruction, warranty, and version up. The goal of the decision-maker (selection of a software package) is represented by the entire area (the base rectangle). For each criterion, the screen area is sliced (either horizontally or vertically) to create smaller rectangles with areas proportional to their relative importance or weight. Each criterion is then diced into sub-criteria recursively, with the direction of the slicing switched 90 degrees for each level. The user can identify any criterion by labels displayed in the offset areas, which are also helpful in recognising the hierarchal structure of the decision problem. The “hook” and “pump” tools (upper right in Figure 3.2) enable users to resize the areas (i.e. change the weights) by pulling on a boundary or by pumping up an area. On the bottom of the display, the horizontal bars show the total score, and as users hook or pump areas the bars change.

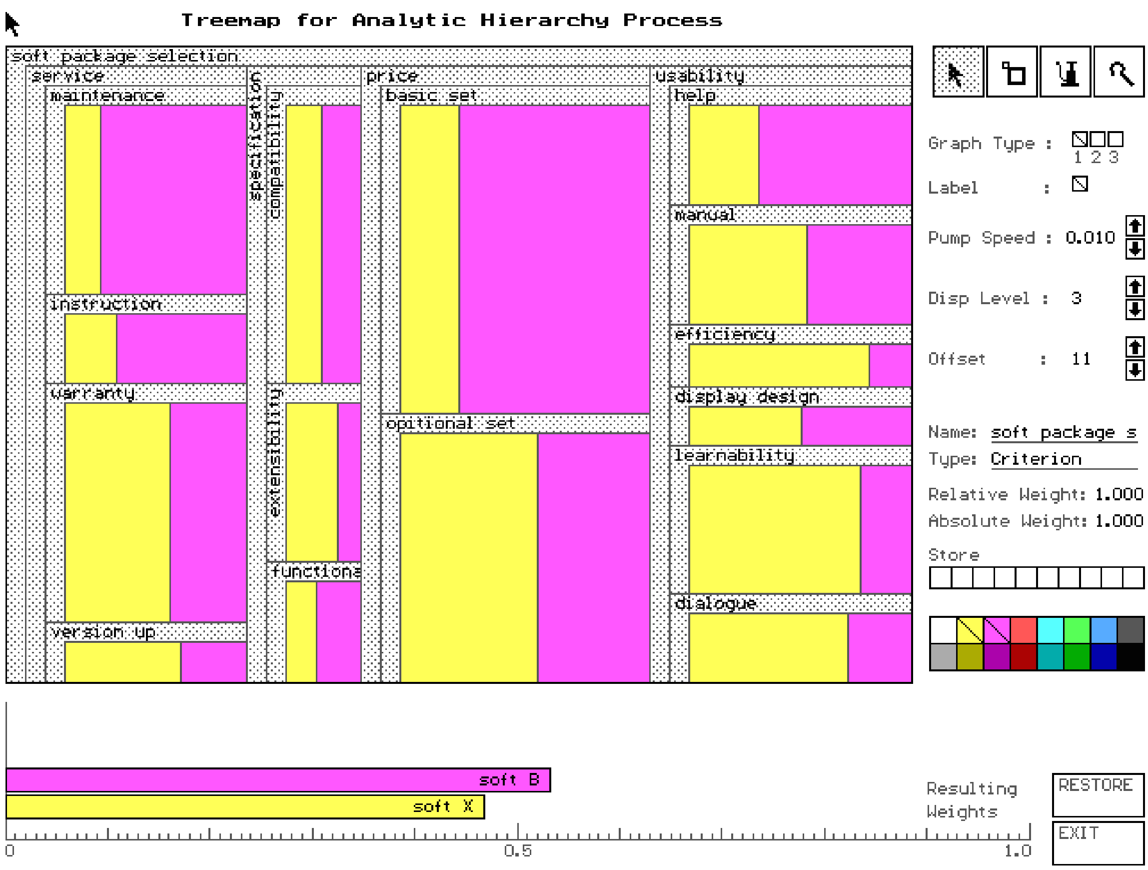
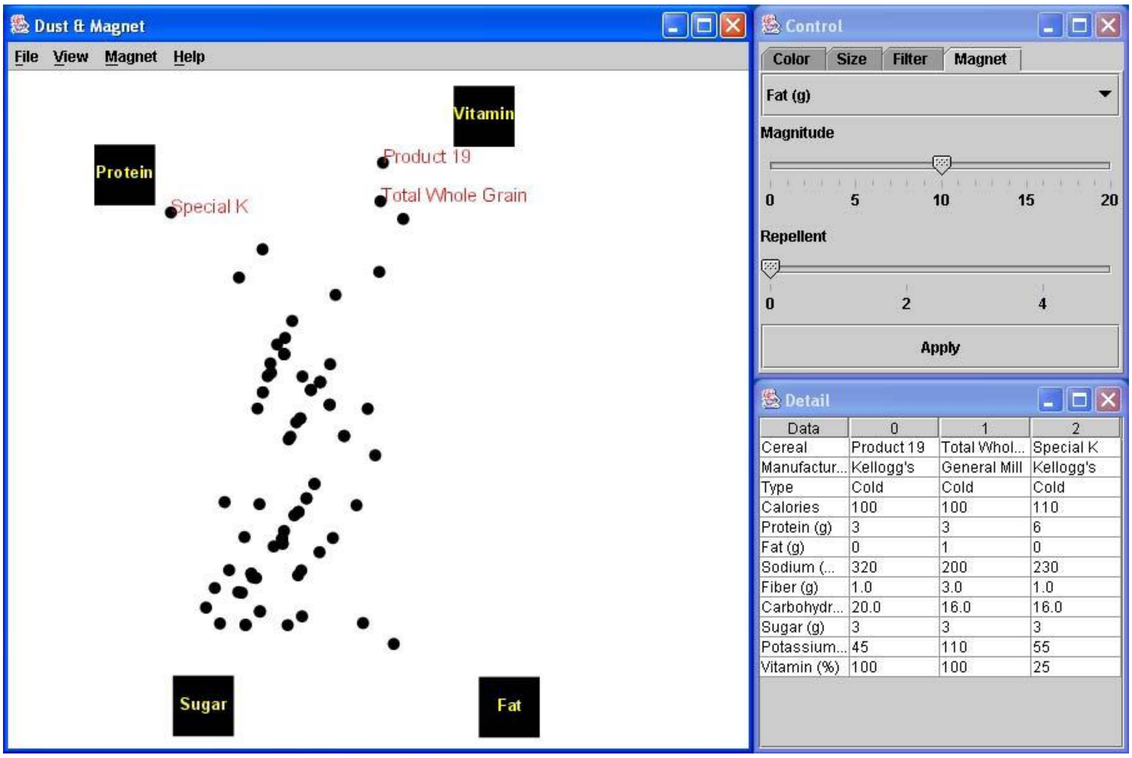


Figure 3.2: An example of a TreeMap generated for a decision problem of selecting a software package based on AHP (source: Asahi *et al.*, 1995)

The primary advantage of representing the AHP with a TreeMap is that the entire problem space is shown at once, while still allowing experimentation with "what-if" scenarios by changing a criterion weight. However, these "what-if" scenarios are based on a change of only one variable at a time, while keeping all other variables fixed at particular values. Furthermore, the AHP TreeMap does not take into account the uncertainties in the criteria themselves and their propagation through the AHP model. Consequently, it is unable to provide decision-makers with a complete picture of all uncertainties and their potential effects on decision-making.

Another InfoVis tool that is designed and applied to support decision-making is Dust & Magnet (Yi et al., 2005). Figure 3.3 shows a screenshot of the Dust & Magnet tool. Dust & Magnet is a multivariate visualisation tool that uses a magnet metaphor to support the multi-attribute decision-making based on the weighted additive (WADD) decision rule (Keeney *et al.*, 1999). Using the WADD rule, each alternative is given a total score based on multiplying the value of each attribute with its relative importance (subjective weight or probability) and summing these weighted attributes values over all attributes. The alternative with the "best" score is chosen as the optimal solution.



Data	0	1	2
Cereal	Product 19	Total Whol...	Special K
Manufactur...	Kellogg's	General Mill	Kellogg's
Type	Cold	Cold	Cold
Calories	100	100	110
Protein (g)	3	3	6
Fat (g)	0	1	0
Sodium (...	320	200	230
Fiber (g)	1.0	3.0	1.0
Carbohydr...	20.0	16.0	16.0
Sugar (g)	3	3	3
Potassium...	45	110	55
Vitamin (%)	100	100	25

Figure 3.3: A screenshot of the Dust & Magnet generated for a decision problem of choosing a cereal (source: Yi *et al.*, 2005)

As shown in Figure 3.3, the decision problem is to choose a cereal from among a list of 77 cereals based on 12 attributes including protein, vitamin, sugar, fat, and others (refer to Yi *et al.* (2005) for complete description of the decision problem). The attributes are represented as black squares and work as magnets, whereas the alternatives are represented as black dots and work as dust particles. The size of the magnet represents the weight of the related attribute. The position of the magnet in the display area represents how high the value of the related attribute is. For example, if the user seeks cereals that have a high level of protein and vitamins, the user can place the protein and vitamin magnets toward the top of the display area. The user can drag one of the magnets using a mouse. As the magnet is being dragged, all of the dust particles are attracted toward this magnet. The level of attraction between the dust particle and the magnet is determined based on the value of the dust particle (the total score of the alternative) and the size of the magnet (the weight of the attribute).

The Dust & Magnet metaphor is an intuitive representation of the weighted additive (WADD) decision rule. In addition, it is engaging and easy to understand because it involves animated interaction. However, it is designed and applied based on a predetermined approach to decision-making (i.e. WADD). This forces the decision-maker to follow the formalism of the prescribed approach to arrive at his or her final decision. In practice, however, the approach to decision-making is usually developed while solving the decision problem rather than being formally prescribed (Payne et al., 1993).

Another multivariate InfoVis technique that is designed to support decision-making based on the weighted additive decision rule (WADD) described above is ValueCharts+ (Bautista & Carenini, 2006). In addition to WADD, the design of ValueCharts+ is based on the decision analysis process proposed by Clemen & Reilly (2001), which is described in Section 2.4 (Figure 2.3). ValueCharts+ utilises the cognitive tasks identified in the PVIT model (shown in Figure 3.1) as a basis for the design and evaluation. It displays the decision alternatives and evaluation attributes in a tabular paradigm and uses horizontal bars to represent values.

Figure 3.4 shows a screenshot of the ValueCharts+ applied to a multi-attribute decision problem of selecting a hotel from among 6 hotels based on a set of attributes including the location, price, room-size, distance from skytrain, and internet access. Each row represents an alternative and each column represents an attribute. The attributes are arranged hierarchally and presented at the column heading of ValueCharts+. The width of each column indicates the relative weight assigned to each attribute. The horizontal bar at each cell depicts the alternative's preference value of a particular attribute, with a filled cell representing the best possible value and an empty one representing the worst possible value. These bars are then accumulated and presented in a separated display in the form of horizontal stacked bars, representing the total score of each alternative.

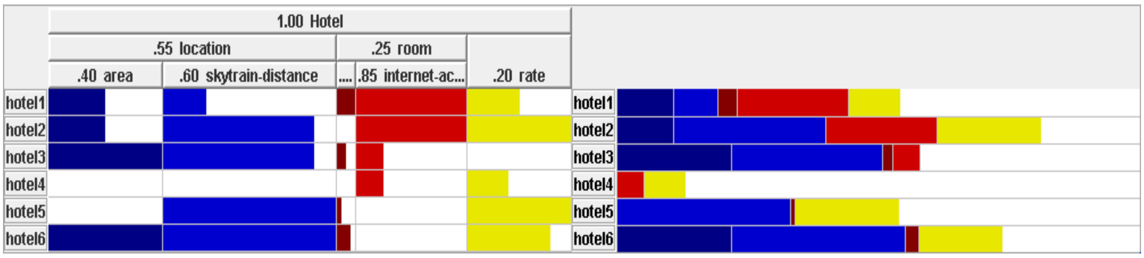


Figure 3.4: An example of ValueCharts+ designed to support a decision-making problem of choosing a hotel (source: Bautista & Carenini, 2006)

An interesting feature of ValueCharts+ is that the weights of attributes can be adjusted by resizing the width of the columns heads. In this way, ValueCharts+ allows the performance of "what-if" analysis of changing an attribute's weight on the total score of each alternative. However, it has the same limitations as AHP TreeMap; the "what-if" analysis is based on a limited number of scenarios which are based on a small change of one attribute weight at a time. It also does not facilitate performing "what-if" analysis of changing the attributes values themselves and exploring their effect on decision-making.

More recently, two multivariate InfoVis techniques, Decision Map and Decision Table (Yi, 2008), have been developed based on ValueCharts+. These two techniques were developed to complement each other in supporting a decision-making problem related to selecting a nursing home based on a set of attributes including the location, cost, security, and the quality of care. Figure 3.5 shows a screenshot of the Decision Map prototype. The Decision Map is inspired by HomeFinder (Williamson & Shneiderman, 1992) and uses a web-based interactive map similar to Google Map[2] and Yahoo Map[3]. Thus, the interface of the prototype is similar to a Google or Yahoo map in addition to using the same interaction techniques. The Decision Map prototype provides geographic information related to the location of the nursing homes (the alternatives) and the distance between each nursing home and the anchor location of the decision-maker.

[2] http://maps.google.com
[3] http://maps.yahoo.com

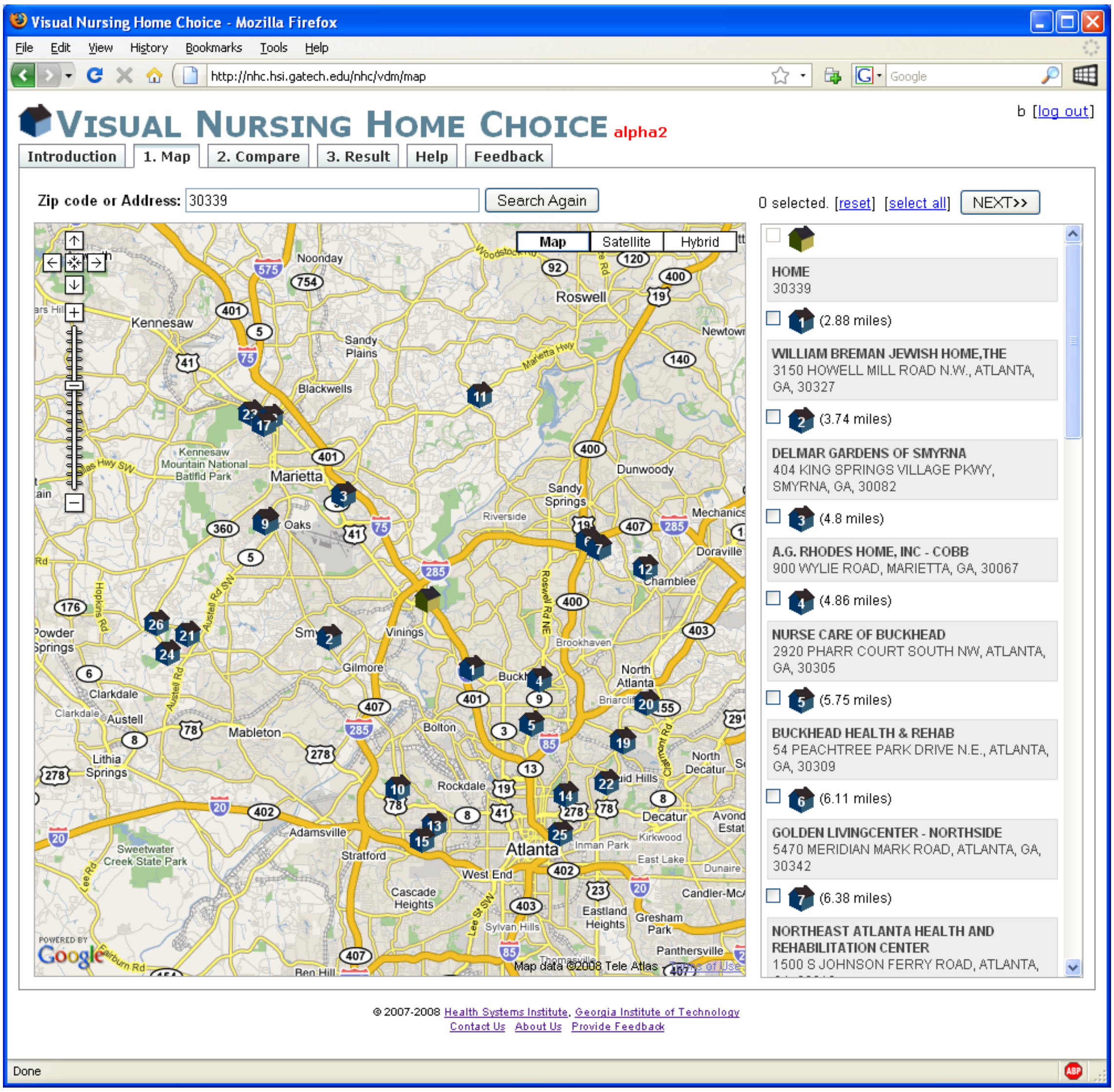


Figure 3.5: A screenshot of the Decision Map protoype (source: Yi, 2008)

On the other hand, the Decision Table prototype shown in Figure 3.6 displays the information in a tabular form with rows representing the available alternatives and columns representing their attributes. This prototype uses horizontal bars to represent attributes values. The designer provided some interactive features to the prototype, such as the use of a weighting slider bar, a distribution view, zooming in/out, and a sorting feature. These features are intended to support some decision-making tasks, such as filtering out uninteresting alternatives, finding extremum, identifying trends, and characterising distribution. Missing values of attributes are given a value of zero and then represented by empty cells.

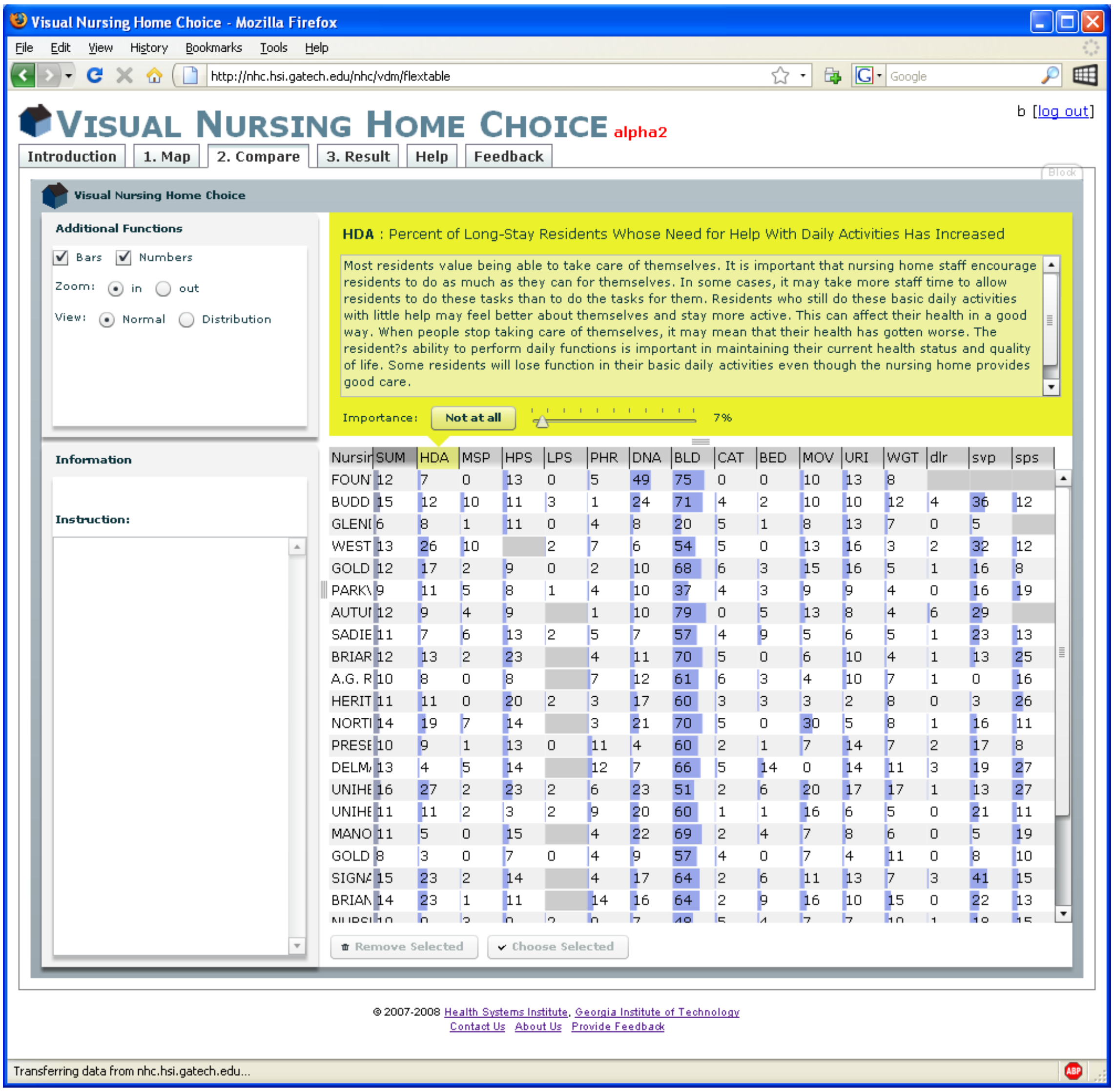


Figure 3.6: A screenshot of the Decision Table prototype (source: Yi, 2008)

A different, but very common visual and analytical decision support tool is the decision tree (Hespos & Strassmann, 1965; Quinlan, 1987, 1990). Figure 3.7 is an example of a decision tree representing a decision problem consisting of two investment alternatives. A decision tree displays the set of all possible decision alternatives, the scenarios and potential outcomes that would result from each decision alternative, and the consequences that may follow each alternative. It begins with what is termed a root node that encodes the decision problem. The other nodes of the tree represent either a decision node (square icon) or a chance node (circle icon). The decision node distinguishes the various decision alternatives, whereas the chance node distinguishes the possible states of nature (i.e., possible values of a decision variable/parameter). The branches of the tree represent either an act of making a decision or an alternative scenario that might occur. The number on each branch indicates the probability of occurrence of the related state of nature. Each combination of decisions and states of nature has outcome associated with it (e.g., net present value, as in the example shown in Figure 3.7).

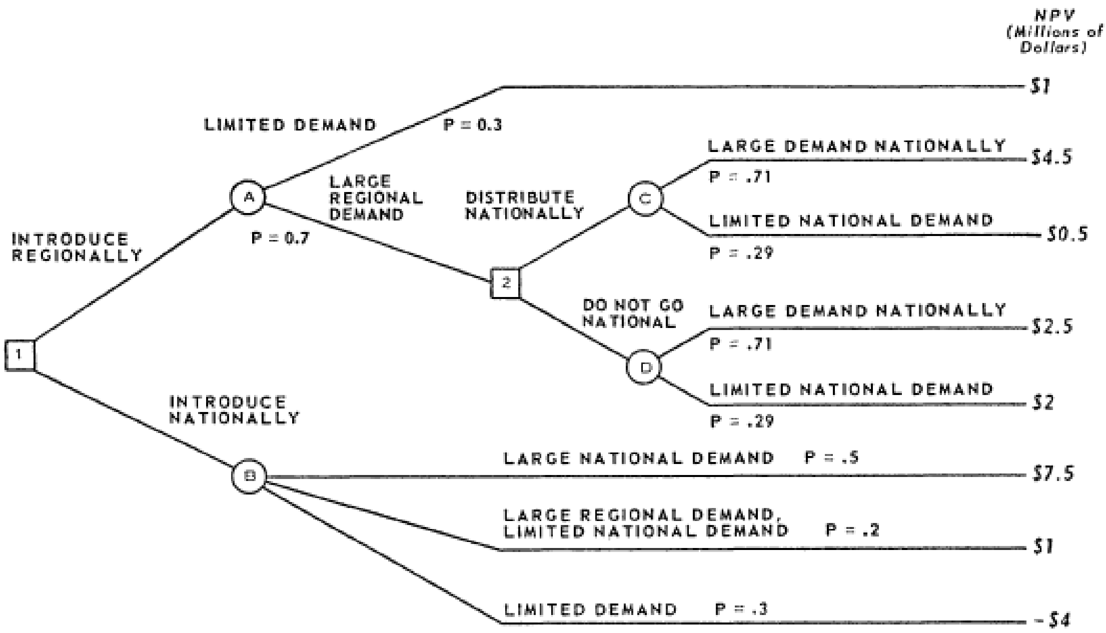


Figure 3.7: An example of using a decision tree to analyse investment alternatives for a new product introduction (source: Hespos & Strassmann, 1965)

Decision trees are most often used for analysing sequential decision problems in situations of uncertainty and risk such as medical diagnosis. They can help decision-makers analyse the decision situation and select the most favourable alternative. When it represents the internal information of a decision problem, a decision tree provides an overview of all the possible choices for decision-makers as well as specific details on the consequences of any particular choice. A decision tree may contain as many nodes as practically possible given human tolerance and processing limitations. Therefore, it is convenient to present and analyse very small decision problems with one or few paths; a large decision tree may become cumbersome and complex. Also, because the decision tree involves the explicit use of statistics, it cannot be easily used by ordinary people who do not have the technical expertise to fully understand the statistical results.

3.3.3 Interaction techniques

Information visualisation systems have two main components: representation and interaction (Yi *et al.*, 2007). The representation component concerns the way that data is mapped and rendered to produce a visual form. The interaction component allows the user to manipulate and explore the represented information to discover new insights.

Interaction techniques have important implications for supporting decision-making. They enable decision-makers to control and navigate the decision problem space. By interacting with the visual representation of the decision problem, interactive InfoVis tools may enhance the matching between the task and the decision environment, which should improve the decision quality and reduce the effort required (Lurie & Mason, 2007). Interaction techniques also enable the decision-maker to restructure the representation of information (Coupey, 1994) and select what to and not to display (Card *et al.*, 1999). This can be done by interactively changing which variables to display, the range of values shown, and whether these variables are displayed using colours or shapes. By providing the decision-maker with more control over the information displayed, interactive InfoVis tools can improve the ability of decision-makers to manipulate and use information in performing various tasks, thereby making better informed decisions.

Interaction techniques have received considerable attention in information visualisation research (e.g., Buja *et al.*, 1991; Dix & Ellis, 1998; Lam, 2008; Tweedie, 1997; Yi *et al.*, 2007). Several techniques have been developed to facilitate various types of interactions. For example, Shneiderman (1996) summarises seven types of low-level interaction techniques: overview, zoom, filter, detail-on-demand, relate, history, and extract. Yi *et al.* (2007) categorise interaction techniques based on the user intention into: select, explore, reconfigure, encode, abstract/elaborate, filter, and connect. Two commonly used techniques that have been covered in many information visualisation books are the overview+detail and focus+context (Cockburn *et al.*, 2008).

The overview+detail technique displays the information space in multiple separate views. One view provides an overview of the information space and the others shows details about the part of the information that the user is interested in (Cockburn *et al.*, 2008). This technique is effective when the amount of information surpasses the resolution of a computer screen. For example, when the information required in the decision-making process does not fit in the visible area, it is cognitively better to split the area into an overview and a detail view. The information that is needed in the first phases of decision-making (e.g., comparisons and selections of alternatives) could be shown on the overview. Subsequently, the decision-maker can then look at the details (e.g., analysis and evaluation of a selected alternative). The detail view contains more information about the highlighted/selected alternatives shown in the overview.

In contrast, the focus+context technique integrates detail (focus) and overview (context) into a single display where all parts are simultaneously visible (Cockburn *et al.*, 2008). This technique often includes intentional distortion between the focused area and surrounding areas (Yi, 2008). Several focus+context techniques have been devised. One example is the fisheye view, a distortion technique that acts like a wide-angle lens to amplify the area of interest (Sarkar & Brown, 1994). Another common example is the Cone Tree (Robertson *et al.*, 1991), where visual objects at the front appear larger than those at the back. Other common focus+context techniques include filtering, highlighting, and selective aggregation (Card *et al.*, 1999).

Several other interaction techniques are also common and might be effective for supporting different decision-making tasks. For example, finding of items can be facilitated by zooming and filtering. Filtering out uninteresting alternatives or getting alternatives details can be supported by dynamic query. Keeping track of particular information (e.g., a decision alternative or particular scenario) and comparing alternatives can be supported by marking or highlighting.

3.3.4 Evaluation of InfoVis tools for decision-making support

The maturity of information visualisation research has led to the expansion and commercialisation of many techniques for the purpose of decision-making support (such as those from Spotfire[4], Inxight[5], and SmartMoney[6]). However, the adoption of InfoVis techniques in decision-making support is still a novelty for many users (Plaisant, 2004; Zhu & Chen, 2008). In order to understand the potential and limitations of a new InfoVis technique, evaluation is an essential and ongoing activity in the development process.

[4] http:// spotfire.tibco.com
[5] http://www.inxight.com
[6] http://www.smartmoney.com

In spite of the extensive work on information visualisation to support decision-making, very few evaluation studies have been reported in the literature. In our investigation, we have identified the following evaluation studies:

Bautista & Carenini (2008) conducted an empirical evaluation for two orientations (horizontal and vertical) of the ValueCharts+ which is described in Section 3.3.2. In their study, the authors gave subjects a decision problem of choosing hotels in Vancouver. They utilised a set of primitive tasks adapted from the Preferential choice Visualisation Integrated Task (PVIT) model (see Figure 3.1). They used time to completion, correctness of tasks, users' satisfaction, and level of confidence as measures to assess the efficacy of the ValueCharts+ and to compare between the horizontal and vertical orientations of the ValueCharts+. While the study demonstrated the strengths and weaknesses of those two orientations, there were no significant differences in overall user performance across them.

Yi (2008) conducted a controlled experiment to demonstrate the effectiveness of the Decision Map and Decision Table that were designed to support a set of compensatory and non-compensatory decision strategies (see Figure 3.5 and Figure 3.6). Two versions of the Decision Map and Decision Table were compared through a web-based experiment. One version is the prototype with a weighting slider bar and sum column to support compensatory decision rules. The other version is a distribution view of the prototypes to support non-compensatory decision rules. In addition, the amount of information was also varied to reveal any interaction between the two versions of the prototypes and the severity of information overload. The amount of information was varied in two ways: varying the number of attributes and varying the number of alternatives. A dataset related to the selection of a nursing home based on multiple attributes was used. Two measures were used in this experiment: the decision quality and perceived usability. The decision quality was measured by quantitative measures (i.e., decision accuracy, time to make decisions) and qualitative measures (i.e., the level of satisfaction, confidence, confusion, and time pressures). The perceived usability was measured with the perceived ease of use, the perceived usefulness, the intensity of flow (involvement), the intensity of flow (control), and aesthetic quality. The results showed that the proposed InfoVis techniques (Decision Map and Decision Table) did not increase the decision quality and perceived usability while the smaller number of attributes or alternatives increased the decision quality and perceived usability.

Generally, the aforementioned studies adopted a quantitative evaluation approach and relied on primitive tasks (e.g., locate and identify). They also used measures such as time to completion, error rate, and users' satisfaction as measures to demonstrate the strengths and weaknesses of the visualisation techniques. Results from such quantitative studies of evaluation could benefit the design of InfoVis techniques. However, evaluation of visualisation's efficacy using simple tasks might not translate easily into improved decision-making outcomes and quality (Zhu & Chen, 2008). Moreover, these studies only focus on how well users performed predefined tasks using the InfoVis tools but they did not address the utility of these tools; i.e. how users used them to accomplish tasks and arrive at their final decisions. Thus, such evaluation studies may have a limited contribution to the understanding of how decision-makers use and interact with InfoVis tool.

There is a move towards qualitative approaches of evaluation which are better at capturing users' experiences and understanding while using InfoVis tools. A qualitative approach to evaluation implies essentially an emphasis on the processes and interactions rather than on measurement, such as accuracy, time to completion, or satisfaction, as do the quantitative usability measures. One of the strengths of qualitative studies is the use of different data gathering methods including observation, interviews, and content analysis of written responses of users. Observation and interview data are often recorded as video or audio tapes, resulting in an array of very rich data which is then analysed.

Qualitative methods of evaluation have their limitations (Isenberg *et al.*, 2008; Sheelagh, 2008). Among these is that they are very time-consuming and require intensive labour from the experimenter to gather and analyse data. Another limitation is that there is no guideline to the determination of the sample size. The sample size for qualitative evaluation is often determined during the study and the recruitment of users is stopped once the analysis reaches a "saturation" point; i.e. the point at which further analysis would not lead to new results (Patton, 2005). However, there is no guidance to say when the saturation point may occur (Carpendale, 2008). Moreover, the experimenter's subjectivity and experience affects the quality of the data gathered, and may lead to bias in the analysis of results (Isenberg *et al.*, 2008).

3.4 Application of information visualisation in areas related to decision-making

3.4.1 Uncertainty visualisation

There is now increasing agreement that the uncertainty in the information and its implications should be incorporated into the decision-making process and presented in a manner that is comprehensive and unambiguous (Liere *et al.*, 2009).

Many techniques have been developed over the last decade for uncertainty visualisation, particularly by the geographical and scientific visualisation communities (Liere *et al.*, 2009; MacEachren *et al.*, 2005; Pang *et al.*, 1997; Thomson *et al.*, 2005). Pang *et al.* (1997) propose a toolbox of effective techniques for uncertainty visualisation in scientific visualisation. Many of these techniques can also be used in information visualisation. They include adding glyphs, adding geometry, modifying geometry, modifying attributes, animation, sonification, and psycho-visual approaches.

3.4.2 Risk visualisation

Many real world decision problems involve risk. In such situations, the comprehensive understanding of risk and its characteristics is vital. According to (Lipkus & Hollands, 1999), users might wish to extract the following information regarding risk: 1) risk magnitude (i.e., how large or small the risk is); 2) relative risk (i.e., comparing the magnitude of two risks); 3) cumulative risk (i.e., observing trends over time); 4) uncertainty (e.g., estimating amount of uncertainty and variability or range of scores); or 5) interactions among risk factors.

Most of the research on risk visualisation has focused on the use of statistical diagrams such as histograms (or bar charts), pie charts, scatter plots, and line graphs to display risk (Bostrom *et al.*, 2008; Edwards *et al.*, 2002; Lipkus, 2007; Lipkus & Hollands, 1999). Different types of icons, such as stick figures, faces, asterisks, and dots, have also been used extensively to aid relative risk judgments (Edwards *et al.*, 2002; Lipkus, 2007). Furthermore, several authors have explored the potential of interaction and animation to highlight aspects of risk and assess risk factors (e.g., Strecher *et al.*, 1999; Wright, 1999). For example, Wright (1999) used movement of a curve to assess market risk due to a change in interest rates.

Colours also are widely used in risk visualisation as a means to attract people's attention and highlight levels of risk (e.g., red and dark orange to represent high risk) (Wolfe & Horowitz, 2004). Several studies have addressed the influence of colours on risk perception and decision-making processes (Lipkus & Hollands, 1999; Rogers & Groop, 1981; Soldat & Sinclair, 2001; Wogalter *et al.*, 2002). A study by Wogalter *et al.* (2002) supports the following hierarchy of colours to convey risk level: red/dark orange riskier than yellow, yellow riskier than green. Scaling based on lightness or brightness may also be helpful in presenting risk information (Bostrom *et al.*, 2008). Davis and Keller (1997) asserted that the use of colour hue and saturation are the "best candidates" for presenting risk information using static methods. Brewer (2006) advises the use of light-to-dark colour for low-to-high values of risk with a constant hue.

3.4.3 Sensitivity analysis visualisation

Graphical methods for sensitivity analysis provide a means for presenting the results of sensitivity analysis in the form of graphs, charts, or surfaces (Mokhtari & Frey, 2005). Generally, they are used to display the relationships between the output and input variables (Cooke & Van Noordwijk, 2000). In addition, they can be used as a screening tool to guide the selection of appropriate sensitivity analysis methods. They can also complement mathematical and statistical approaches to sensitivity analysis (Christopher Frey & Patil, 2002).

Within the field of information visualisation, multivariate information visualisation is probably the category most relevant to sensitivity analysis (Daradkeh *et al.*, 2008). Despite the large number of multivariate visualisation techniques available, there are few that are applied to sensitivity analysis. In previous work, Daradkeh *et al.* (2008) presented a review of some of the known approaches where visualisation is used for sensitivity analysis. These techniques include the tornado diagram (Cooke & Van Noordwijk, 2000), scatter plots and scatter plot matrices (Hand *et al.*, 2001), radar graphs (Cleveland, 1993), and parallel coordinates (Inselberg & Dimsdale, 1990).

The tornado diagram is probably the most frequently used graphical approach (Abdellaoui *et al.*, 2008; Clemen & Reilly, 2001; Eschenbach, 1992; Howard, 1988). It is used to display the results of local sensitivity analysis; i.e. the effect of changing one variable at a time, while holding all other variables constant (refer to Section 2.4.1). As shown in Figure 3.8, the tornado diagram consists of stacked horizontal bars, where each bar corresponds to one input variable and represents the range of possible outcomes, as the variable is varied over its specified range, while all other variables remain constant at their nominal values. The length of the bar indicates the variable's effect on the model's output. The left and right bar ends indicate the corresponding upper and lower bounds of the possible outcomes. The model output has a nominal value which is calculated for the nominal values of all the input variables and displayed as a vertical line on the diagram.

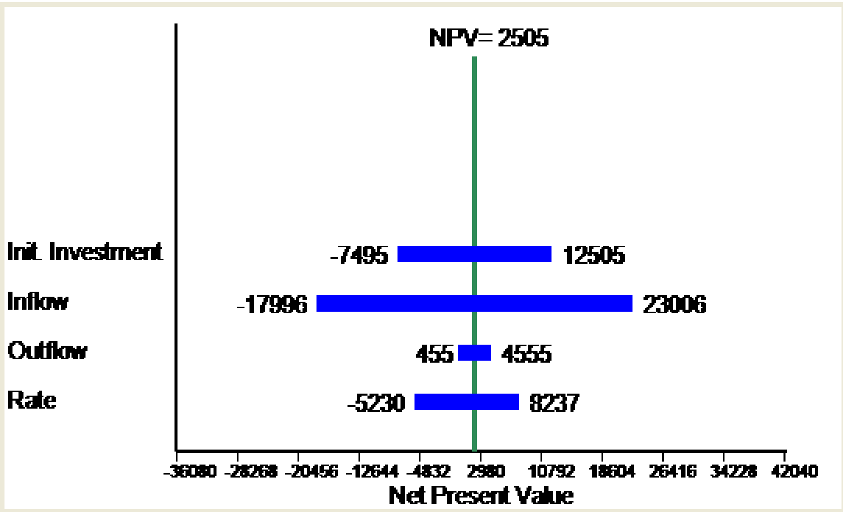


Figure 3.8: Tornado diagram shows the sensititvity of NPV to the variation in each input variable while other variables are held constant

A tornado diagram highlights those input variables to which the outcome is most sensitive. Thus, it informs the decision-maker on the key uncertainties that hinder the decision-making and possible outcomes of these uncertainties. For example, Figure 3.8 shows that, for the given values of the other variables, the outcome (net present value) is mostly influenced by varying the cash inflow, while the variation in the cash outflow has little effect on the outcome.

One of the main drawbacks of the tornado diagram is that it assumes all of the input variables are independent. Thus, it ignores the influence of the interaction between input variables that might have a significant effect on the outcomes (Koller, 2005). In addition, it is a static representation of the sensitivity and thus it doesn't allow decision-makers to explore and compare possible outcomes under different scenarios and so discover the relationships between the input variables and outcomes (Daradkeh *et al.*, 2008; Eschenbach, 1992). For example, the user might wrongly conclude that a decrease in an input variable could result in a decrease in the outcomes whereas the opposite could be true. In the example shown in Figure 3.8, the decrease in the cash outflow increases the net present value. Such useful information cannot be discovered unless some interaction is provided.

3.5 Summary and dicussion

Information visualisation can play various roles to support informed decision-making under uncertainty and risk. Through its numerous cognitive and communicative advantages, information visualisation provides an effective means for depicting information in a way that makes it amenable to analysis and exploration. It can facilitate the integration of uncertainty into the decision-making process, and raise the awareness of decision-makers about its effect. It also can enhance the ability of decision-makers to process and comprehend information, thereby making more informed decisions.

Over the past two decades, several InfoVis tools have been developed to support decision-making in many different areas. However, there are a number of limitations that significantly affect their ability to adequately support informed decision-making under uncertainty and risk. Firstly, although the uncertainty and risk are key elements in realistic decision-making, they have often been neglected or treated in a superficial way. Most of the InfoVis tools are designed and applied based on the assumption that the information available to decision-makers is deterministic and certain. Noted examples include AHP TreeMap, ValueCharts+, and Decision Table, which are described in Section 3.3.2. However, most real-world decision problems typically involve uncertainty and risk which if not considered could result in infeasible and less informed decisions. What is still needed is a consistent and integrated approach for depicting uncertainty and its implications for the information on which decisions are based.

Secondly, although sensitivity analysis is an important part of the decision-making process, it has received limited consideration in many InfoVis tools designed to support decision-making. Many of these tools focus on investigating the relationship between uncertainties in the criteria weights and the subsequent alteration that may occur in the ranking of alternatives. For example, AHP TreeMap and ValueCharts+ allow performance of “what-if” analysis of changing a criterion weight on the total score of each alternative. However, they do not consider uncertainties in the values of input variables and propagation of such uncertainties through the models and criteria used in decision-making. Moreover, they usually only allow sensitivity analysis to be applied locally rather than globally. For detailed discussion of local sensitivity analysis and its limitations, refer to Section 2.4.1.

Lastly, many InfoVis tools focus on presentation rather than analysis and exploration of the uncertainties and risks associated with each alternative. For example, the tornado diagram discussed in Section 3.4.3 provides a static presentation of uncertain input variables and their corresponding range of possible outcomes. However, it does not provide a mechanism to enable decision-makers to interact with the model used to produce these outcomes and then explore possible outcomes under different combinations of values of input variables.

In summary, this review of the literature demonstrates that research into the area of information visualisation to support informed decision-making under uncertainty and risk requires further exploration. Owing to the nature of decision-making under uncertainty and risk, information visualisation to support decision-making faces special challenges such as dealing with uncertainty and its integration into the decision-making process. Focusing on this area of research, the next chapter discusses the information requirements and considerations that need to be addressed when designing InfoVis tools to support informed decision-making under uncertainty and risk.

CHAPTER 4
ANALYSIS OF INFORMATION REQUIREMENTS AND DESIGN CONSIDERATIONS

4.1 Introduction

This chapter discusses the information requirements and main considerations underpinning the design of InfoVis tools presented in this thesis. It also examines what types of information are required by decision-makers to be better informed during the decision-making process.

As discussed in Chapter 2, decision-making under uncertainty and risk is usually described as a process of choosing between alternatives, each of which can result in one of many possible outcomes. These outcomes reflect the uncertain and stochastic nature of decision input variables and their propagation through models and criteria used in the decision-making process. Typically, not all possible outcomes are equally desirable to decision-makers. Consequently, risk accompanies decisions because there is a chance that the decision made can lead to an undesirable rather than a desirable outcome.

Based on this description and the review of the literature on decision-making in Chapter 2, there are two main considerations that constitute the basis for the design of InfoVis tools presented in this thesis. Firstly, in the presence of uncertainty and risk, there is no guarantee that a reasoned decision will necessarily lead to good outcomes. Thus, reasoned decisions cannot be judged as right or wrong; rather, reasoned decisions are those that are well-informed and consistent with the decision-maker’s objectives and preferences. Secondly, to enable informed decision-making, the uncertainty and its associated risk should be explicitly considered and addressed from the beginning of the decision-making process as an integral part of the information on which decisions are based.

The intention of the InfoVis tools proposed in this thesis is to support informed decision-making under uncertainty and risk. In addition, they aim to facilitate the integration of uncertainty into the decision-making process, and raise the awareness of decision-makers about its effects on their decisions. The following sections discuss in more detail these considerations and the roles that InfoVis tools can play to support them.

4.2 Informed decision-making (IDM)

There are many different definitions of informed decision-making offered in the literature (refer to Section 2.5 and van den Berg *et al.*, 2006). All these definitions have two prominent dimensions in common. Firstly, informed decision-making is based on the availability of adequate and relevant information about all elements of the decision problem. Secondly, it is based on the ability of decision-makers to process and utilise this information to arrive at final decisions that are consistent with their objectives and preferences.

As discussed in Section 2.4, there are many different approaches to decision-making under uncertainty and risk. However, there is no approach that guarantees making a fully informed decision. On one hand, most of these approaches rely on a partial, rather than a comprehensive, processing of available information to produce a final decision. For example, the decision rules of maximax and maximin focus only on one particular piece of information, the extreme outcomes associated with each alternative, but fail to take account of the (possibly very small) likelihood of their occurring. On the other hand, the approach to decision-making is highly-relevant to the decision-maker's choice behaviour and his or her attitude toward the risk (refer to Section 2.4.2). Moreover, in practice the approach to decision-making is usually developed while solving the decision problem rather than being formally prescribed (Payne *et al.*, 1993).

Therefore, the InfoVis tools in this thesis will not be designed on the basis of a prescribed approach to decision-making. Rather, they will be designed to provide decision-makers with information on the basic elements of the decision problem and present this information in a way that makes it amenable to analysis and exploration. The decision-maker can then process and employ this information to perform many tasks of decision-making to arrive at final decisions without being constrained by the formalism of a prescribed approach. Section 4.4 discusses the different types of information decision-makers may require to make informed decisions under uncertainty and risk.

4.3 Integration of uncertainty into the decision-making process

As illustrated in Section 2.4.1, the descriptions of the decision-making process usually include a step for assessing the effect of uncertainty on decision-making. This can be done by performing a sensitivity analysis either before or after choosing a preferred alternative (see Figure 2.2 and Figure 2.3). However, one major limitation in both of these approaches is that the treatment of uncertainty and its effect is often seen as an "add-on" step that can be ignored or trivialised. Moreover, there is no clear mechanism that enables decision-makers to review their decisions in the event of taking decisions that are not consistent with their objectives and preferences.

Another limitation in the decision-making processes discussed in Section 2.4.1 is that the sensitivity analysis usually involves a limited number of "what-if" scenarios. These scenarios are performed based on a small change in only one variable at a time, while keeping all other variables fixed at particular values. This is often called local sensitivity analysis. As discussed in Section 2.4.1, local sensitivity analysis has a number of drawbacks. It cannot take into consideration all possible scenarios and the effect of interaction among different variables on the chosen alternative. Thus, it does not provide decision-makers with a complete picture of all uncertainties and their potential effects on decision-making.

To address these limitations, the uncertainty in the input variables should be treated from the beginning of the decision-making process as an integral part of the information on which decisions are based. Also, the effect of uncertainty on decision-making should be analysed in a comprehensive way. An analysis is comprehensive when it takes into account the entire range of variation of input variables, the interactions between them, and their effect on all possible outcomes associated with the decision alternatives.

A risk-based approach for incorporating uncertainty into decision-making

If uncertainty is incorporated into the decision-making process, the criteria used to assess the performance of decision alternatives should reflect this. It's widely recognised that in the presence of uncertainty, the risk (i.e. the probability of obtaining undesirable outcomes) is a frequently used criterion for exposing the effect of uncertainty and evaluating the decision alternatives (Maier *et al.*, 2008). This is because the probability of obtaining undesirable outcomes offers a clear way to make sense of uncertainty and address it explicitly in the decision-making process (Hammond *et al.*, 1999).

Our approach to making uncertainty an integral part of decision-making is to view the whole process as one of determining the risk (i.e. the probability of undesirable outcomes) associated with the decision. This approach is shown in Figure 4.1 where decision-makers specify the risk criterion to be used and also the uncertainty for each input variable. For example, in the case of considering an investment decision problem, the two components of the risk might be the probability of making a loss and the amount of money that could be lost as a consequence of making a decision. The decision-maker is then interested in both the risk that the investment will make a loss, and how that risk is affected by his or her knowledge of the uncertainties in the variables relating to this particular investment.

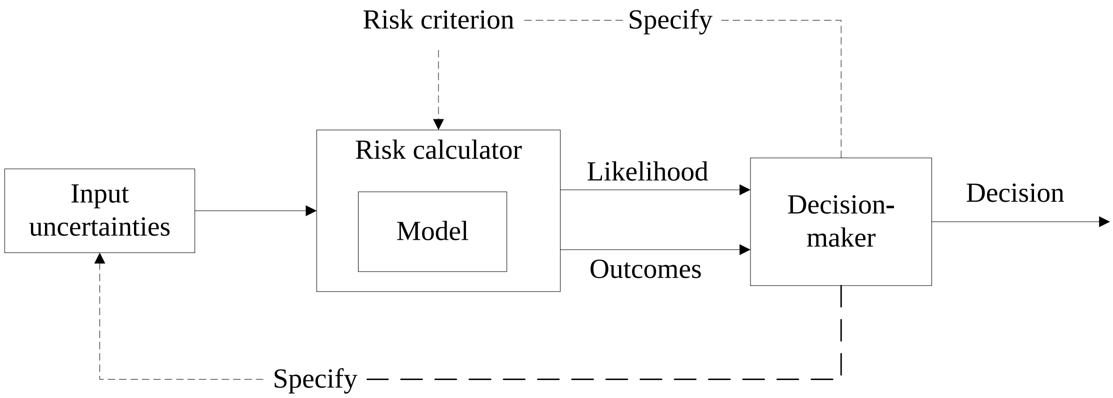


Figure 4.1: The proposed approach for incorporating input uncertainty into the decision-making process.

The proposed method for incorporating uncertainty and the resulting risk into the decision-making process is adapted from the probabilistic risk assessment approach (refer to Section 2.3.2). A probabilistic risk assessment (PRA) approach provides the formalism and technical basis for considering the uncertainties in the estimates of input variables. In the proposed method, the input variables are entered as a range of values, instead of single values. For example, in an investment decision problem, instead of using a single discount rate of 7% in the risk calculation, a range of values would be entered that reflects the uncertainty in the discount rate of the investment. These values are then propagated through the model and combined in such a way as to yield a risk distribution. This distribution represents the range of risks anticipated to exist in the decision alternatives.

4.4 Information visualisation and informed decision-making under uncertainty and risk

As illustrated in Chapter 3, many InfoVis tools have been developed to support decision-making. However, there are a number of limitations that significantly affect their ability to support adequately informed decision-making under uncertainty and risk. Firstly, although the uncertainty and risk are key elements in realistic decision-making, they have often been neglected or treated in a superficial way. Secondly, although sensitivity analysis is an important part of the decision-making process, it has received limited consideration in many InfoVis tools. Thirdly, many InfoVis tools focus more on presentation rather than analysis and exploration of uncertainties and risk associated with available alternatives.

To address these limitations, decision-makers need to be equipped with InfoVis tools that not only inform them about all elements of the decision problem, but also facilitate the interactive analysis and exploration of these elements at varying granularities of detail. This analysis and exploration is central to building understanding of the decision problem and interlinked relationships between its elements. This understanding is a key prerequisite for making well-informed and justifiable decisions.

4.4.1 Information requirements and decision-making under uncertainty and risk

The decision problem under uncertainty and risk is usually characterised as consisting of the following main elements: 1) the set of alternatives from which a preferred alternative is chosen; 2) the uncertain input variables and their possible values; 3) the possible outcomes resulting from uncertainties in the input variables and their propagation through models and criteria used in decision-making; 4) the risk of obtaining undesirable outcomes associated with each alternative (Clemen & Reilly, 2001). All these elements should be taken into consideration when designing InfoVis tools to support informed decision-making. This is because in the presence of uncertainty and risk, decision-makers usually base their decisions not only on the possible outcomes but also on the uncertainty and risk each alternative entails.

As discussed in Section 2.3.2, risk is defined as the probability of obtaining undesirable outcomes. However, informed decision-making requires a thorough consideration of other information pertaining to risk. In his work Payne (1973) specifies four basic dimensions of information that individuals usually use to arrive at decisions where risk is involved. In addition to the probability of undesirable (or negative) outcomes, there are the probability of desirable (or positive) outcomes, and the actual desirable and undesirable outcomes. In the literature on decision-making, information about risk is usually described in two ways; either as a probability distribution over a range of possible outcomes or as four basic dimensions of information (Payne, 1973). For example, to choose between risky investments, one can describe the risk as a probability distribution over amounts of money or as four dimensions of information; i.e. the probability of winning, the amount of the win, the probability of losing, and the amount of the loss.

All four dimensions of information about risk should receive a balanced consideration when designing InfoVis tools to support making informed decisions (Dolan & Iadarola, 2008). This is because providing decision-makers with only information on, for example, undesirable outcomes or their probabilities could cause them to be biased towards this information, and consequently overlook potential desirable outcomes or opportunities (Payne & Braunstein, 1978). Our approach to addressing uncertainty and its associated risk discussed in Section 4.3 captures all possible outcomes; the desirable and undesirable ones as well as their relative probabilities. Thereby, it provides decision-makers with a complete risk profile for each alternative. The risk profile captures the essential information about how uncertainties in the input variables affect an alternative. It also provides a consistent basis for comparing these uncertainties; thereby allowing decision-makers to focus on key uncertainties that might significantly influence the consequences of their decisions.

4.4.2 Analysis and exploration of alternatives at different levels of granularity

In addition to all aforementioned information, decision-makers need to be able to explore and compare alternatives at different granularities of detail. The presence of uncertainty in the values of input variables implies that there are many possible realisations (or values) for each input variable. This gives rise to the presence of many possible scenarios, where each scenario represents a possible combination of all values of input variables, one for each variable (Marco *et al.*, 2008). The set of possible scenarios captures all possible outcomes and the range of uncertainties and risk anticipated.

The InfoVis tool should provide facilities for generating possible scenarios and conducing analysis based on the generated scenarios. This requires facilities for enabling decision-makers to provide their own estimates of the values for each uncertain variable and its distribution. In addition, it requires the provision of computational facilities for propagating all uncertainties through models and criteria used in decision-making. Once all uncertainties are propagated through models, the InfoVis tool should then provide decision-makers with a complete picture of the generated scenarios and the distribution of uncertainties and risks anticipated to exist in these scenarios. At the same time, it should allow decision-makers to interact with the decision model for experimenting with possible "what-if" scenarios and explore the outcomes and risk associated with alternatives under these scenarios.

4.5 Summary and discussion

Based on the review of the literature on decision-making under uncertainty and risk in Chapter 2, we have identified two main considerations that constitute the basis for the design of InfoVis tools presented in this thesis. Firstly, in the presence of uncertainty, reasoned decisions cannot be judged as right or wrong. Rather, reasoned decisions are those that are well-informed and consistent with the decision-maker's objectives and preferences. Informed decision-making is based on two main dimensions; the availability of information and the ability of decision-makers to process this information. Secondly, to enable informed decision-making, the uncertainty and its effect, i.e. the risk, should be explicitly addressed from the beginning of the decision-making process as an integral part of the information on which decisions are based.

Information visualisation can play an important part in supporting informed decision-making by presenting all necessary information in ways that make it amenable to analysis and exploration. It also can facilitate the consideration of uncertainty and the resulting risk to be better integrated into the decision-making process, thus allowing decision-makers to take advantages of this integration. The next chapter discusses how

InfoVis prototypes were developed based on an iterative design process to support informed decision-making under uncertainty and risk.

CHAPTER 5
DEVELOPMENT OF THE VISUALISATION PROTOTYPES

5.1 Introduction

This chapter discusses how InfoVis prototypes to support informed decision-making under uncertainty and risk were designed, implemented and refined through a pilot evaluation. An iterative design process guided by feedback and suggestions received from users was adopted (Liere *et al.*, 2009). The design process was also based on the design considerations and information requirements of decision-makers discussed in Chapter 4. At an early stage of the design process, two exploratory prototypes, called the Interactive Tornado Diagram and Risk Explorer, were designed and implemented. Both prototypes were mainly intended to facilitate the integration of uncertainty into the decision-making process and inform decision-makers about its consequences (refer to Section 4.3). Then, the exploratory prototypes were evaluated in order to collect feedback from users on the information provided and receive suggestions for further improvement. Based on the users' feedback and suggestions, reinforced by the design considerations and information requirements discussed in Chapter 4, a new InfoVis prototype, called VisIDM, to support informed decision-making (IDM) under uncertainty and risk was developed. The VisIDM prototype was intended to provide information on the basic elements of the decision problem under uncertainty and risk (refer to Section 4.4.1). It was also intended to facilitate the interactive analysis and exploration of these elements at different granularities of detail (refer to Section 4.4.2). The following sections describe these prototypes and demonstrate their practical use through an application example of a financial decision-making problem.

5.2 Application example: financial decision support

The example problem to be explored and visualised is a decision-making scenario of choosing an investment based on uncertain information. Some examples of such a scenario include the decision on whether or not to buy a property for investment and rental income or decision to select from among a set of projects available for investments. In making such decisions, decision-makers usually specify evaluation criteria (e.g. the potential profit and probability of making a loss associated with the investment). They also define the key variables that influence the evaluation criteria and their possible values (e.g. the income from the investment and its running cost). Then, they use a financial model to predict and evaluate the profitability of the investment under multiple scenarios and base their decisions on this evaluation (refer to Section 2.4.1 for further discussion of this process).

To predict and analyse the profitability of an investment, a financial model for investment decision-making called Net Present Value (NPV) is commonly used (Dayananda *et al.*, 2002; Jovanovic, 1999; Magni, 2009; Tziralis *et al.*, 2009). The NPV model is emphasised in many textbooks as a theoretically and practically sound decision model (e.g. Copeland & Weston, 1983; Koller *et al.*, 2005; Magni, 2009). It represents the difference between the present value of all cash inflows (profits) and cash outflows (costs) over the life of the investment, all discounted at a particular rate of return (Magni, 2009). The purpose of NPV is basically to estimate the extent to which the profits of an investment exceed its costs. A positive NPV indicates that the investment is profitable, while a negative NPV indicates that the investment is making a loss. A basic version of calculating NPV is given by equation 5.1:

$$NPV = C_0 + \sum_{t=1}^{n} \frac{(CI_t - CO_t)}{(1+r)^t} \tag{5.1}$$

Where

C_0 is the initial investment.
n is the total time of the investment.
r is the discount rate (the rate of return that could be earned on the investment).
CI_t is the cash inflow at time t.
CO_t is the cash outflow at time t.

As shown in Equation 5.1, in its basic form, the NPV model consists of five input variables. In practice, each of these variables is subject to uncertainty because the information available on their values is usually based on predictions, and fluctuations may occur in the future. In addition, there are interactions between input variables (e.g. discount rate and cash inflow) that can have significant effects on the potential profit outcomes (i.e. NPVs) of the investment. Consequently, the investment decision can lead to many possible outcomes (i.e. different values of NPV). Since not all possible outcomes are equally desirable to the decision-maker, the investment decision involves a degree of risk. The risk is present because there is a chance that the investment decision can lead to an undesirable rather than a desirable outcome.

5.3 Exploratory prototypes

As discussed in Section 4.3, one of the main requirements of informed decision-making is the explicit consideration and integration of uncertainty into the decision-making process. Our approach for making uncertainty an integral part is to view the whole process as one of determining the risk associated with making the decision. The ideas for the InfoVis prototypes were firstly applied to “yes/no” decisions; in this case, to decide on whether or not to proceed with an investment. Two exploratory prototypes were designed and implemented to facilitate the integration of uncertainty and risk into the decision-making process for “yes/no” decisions as described in the next two sections.

5.3.1 The Interactive Tornado Diagram

This InfoVis prototype is an extension to the static Tornado Diagram which is commonly used in decision-making. As discussed in Section 3.4.3, the purpose of the static Tornado Diagram is to display the effect of changing each input variable over its range of uncertainty on the model’s outcomes. One drawback of the static Tornado Diagram is that it cannot take into consideration the effect of interactions between input variables on the model’s outcomes. In addition, it is a static representation of the effect of uncertainty and thus it does not facilitate the exploration and comparison of possible outcomes under different scenarios (i.e. combinations of variables values). To rectify these drawbacks, an interactive version of the Tornado Diagram was developed.

Figure 5.1 shows the Interactive Tornado Diagram prototype. Similar to the static Tornado Diagram, the Interactive Tornado Diagram consists of a set of horizontal bars, each of which is associated with one input variable. Each bar shows the range of possible outcomes as the associated input variable is varied over its specified range of uncertain values while all other input variables remain constant at specific values. The length of the bar indicates the variable’s effect on the model’s outcomes; the longer the bar, the greater the effect is. The vertical green line crossing the horizontal bars represents a specific value of the model's outcome which is calculated for the specific values of all input variables. In addition, the Interactive Tornado Diagram allows the user to provide his or her own estimates of the values for input variables through the text boxes shown at the bottom of Figure 5.1. It also enables the user to change the values of the input variables interactively using the scroll bars.

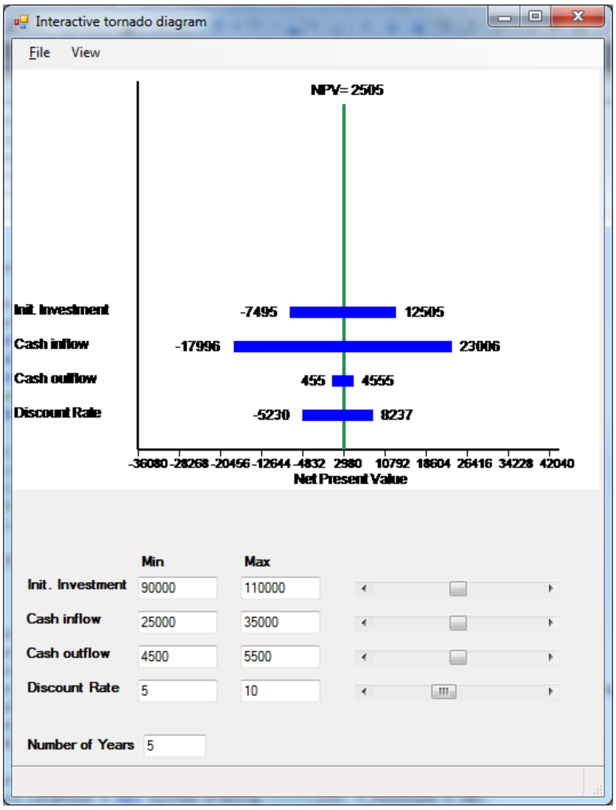
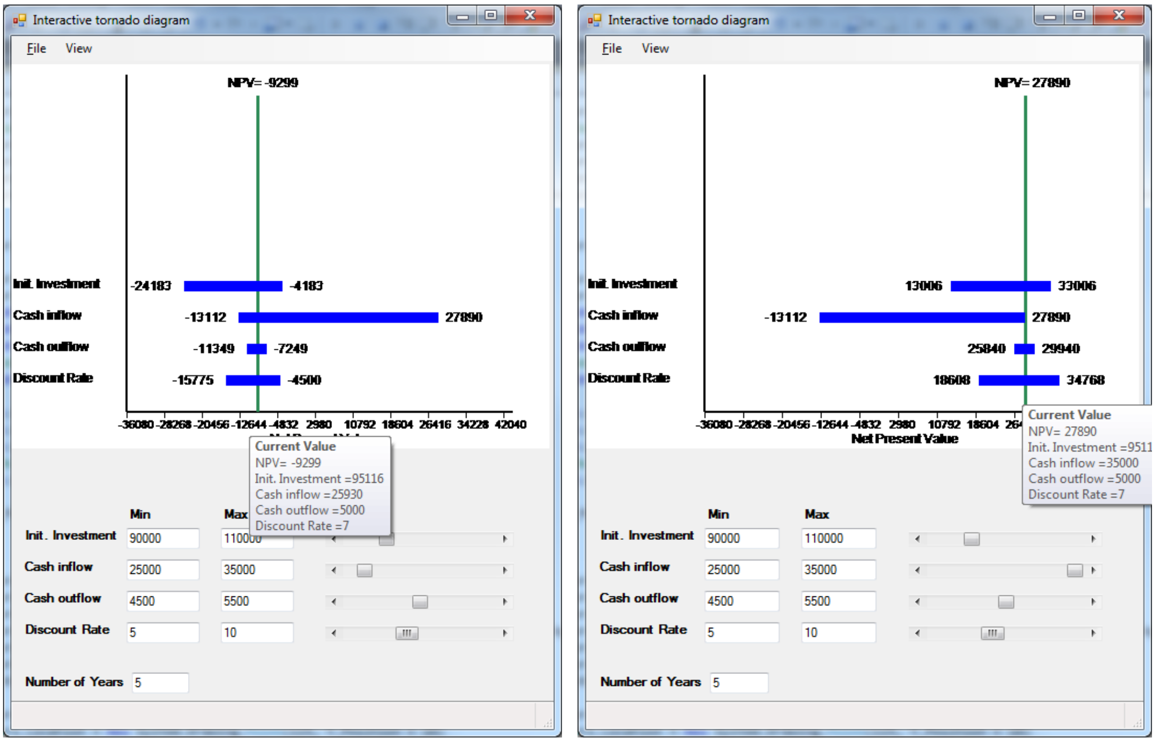


Figure 5.1: A screenshot of the Interactive Tornado Diagram

The Interactive Tornado Diagram helps in exploring the effect of interactions between input variables on the overall outcome uncertainty. This can be investigated by varying an input variable (with its scroll bar) and observing how the horizontal bars on the diagram for the other input variables change. For example, in Figure 5.1, if the decision-maker scrolls the cash inflow scroll bar, he/she will notice that the length of the discount rate bar will change. This means that the uncertainty in the model's outcomes resulting from the variation in the discount rate variable is affected by the cash inflow value, as can be seen from Figure 5.2a and Figure 5.2b. The scroll bars corresponding to input variables also enable the decision-maker to experiment with many different “what-if” scenarios (i.e. combinations of variables values) and explore the model’s outcomes under these scenarios. The decision-maker can then benefit from this analysis and exploration to improve his or her understanding of both the decision problem and the uncertainties. This understanding is a key prerequisite for making informed and justifiable decisions (French, 2003).



a b

Figure 5.2: (a) Influence of decreasing the cash inflow value on the discount rate bar length. (b) Influence of increasing the cash inflow value on the discount rate bar length

A drawback of the Interactive Tornado Diagram is that although it allows the interactive analysis and exploration of possible outcomes, it does not provide insight into the likelihood of these outcomes. Knowing only the possible outcomes is not enough for decision-makers to be informed about the possible consequences of uncertainty in the input variables. They need to evaluate the relative likelihood of the occurrence of possible outcomes and integrate this likelihood into their process of decision-making in a comprehensive and useful way (refer to Section 4.4). To rectify this drawback a prototype of Risk Explorer was developed.

5.3.2 Risk Explorer

The main purpose of Risk Explorer is to allow the decision-maker to explore the risk (i.e. the probability of obtaining undesirable outcomes) and its sensitivity to the variation of the input variables. Figure 5.3 shows a screenshot of the Risk Explorer prototype. It allows the decision-maker to specify the range of values for each input variable through the corresponding text boxes. Then, it portrays the distribution of risk values (i.e. probabilities of undesirable outcomes) in a uniform grid layout. The grid also displays the range of possible values of each input variable divided into a number of divisions (cells in the grid).

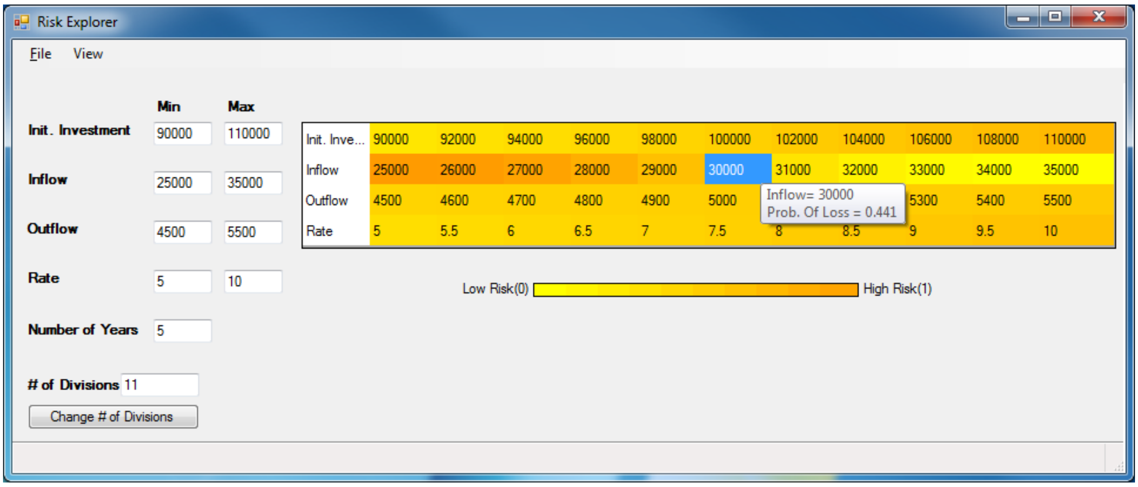


Figure 5.3: A screenshot of the Risk Explorer shows the range of risk (i.e. probability of obtaining undesirable outcomes)

Risk Explorer uses colours to convey the probability of obtaining undesirable outcomes (in this case the probability of obtaining negative values of NPV). The colour of each cell in the grid conveys the probability of obtaining undesirable outcomes associated with the decision alternative based on the variable’s value shown in the cell. Yellow means no risk (i.e. the probability of obtaining undesirable outcomes = 0). Dark orange represents the highest risk (i.e. the probability of obtaining undesirable outcomes = 1). The probability of undesirable outcomes is calculated based on fixing the value in the cell and taking every possible value of all other variables and calculating what proportion of these combinations will result in undesirable outcomes. The numerical values of the risk (i.e. the probability of undesirable outcomes) can be retrieved by hovering the mouse over the cells. For example, the popup window in Figure 5.3 shows that if the inflow is $30000 (highlighted cell) then if considering all other possible combinations of values for the other input variables, about 44% (probability 0.44) will result in the undesirable outcome of a loss.

As shown in Figure 5.3, the Risk Explorer prototype displays the information in a uniform grid which facilitates the presentation of the uncertainty and associated risk of undesirable outcomes in an organised way. It makes it easy to see and follow the change in the degree of risk across the cells, which in turn facilitates the recognition of trends and relationships between the uncertain values of input variables and the probability of undesirable outcomes. Furthermore, all input variables are bounded by their specified maximum and minimum values and all possible values in between are discretised into a finite number of divisions. Therefore, they can be mapped onto equal-sized cells. In this way the decision-maker can run through or compare several scenarios with various values and easily determine the probability of undesirable outcomes at various degree of uncertainty. Colour was chosen for the purpose of presenting the probability of undesirable outcomes because it is widely used for risk visualisation and communication. Also it is an important visual attention guide that can highlight levels of risk (refer to Section 3.4.2).

Providing an overview of the uncertainty and risk of undesirable outcomes

Risk Explorer provides an overview of all possible scenarios (i.e. possible values of input variables) and the probability of undesirable outcomes associated with the decision alternative under these scenarios. By observing the colour variation across the cells, the decision-maker can quickly and easily get an overview of the probability of undesirable outcomes and see whether an alternative is potentially risky or not. In addition, they can readily see the values of the input variables for which the decision alternative is likely to be risky or not. For example, in Figure 5.3, the yellow cells in the second row of the grid show that if the inflow varies within the range [$33000, $35000], the decision-maker can have confidence that there is a very low probability of making a loss associated with the decision alternative if the other variables stay within the specified ranges.

Furthermore, by looking at the displayed range of colours that represents the probability distribution of undesirable outcomes, the decision-maker can recognise the trends of the possible risk values (i.e. probabilities of undesirable outcomes), as well as their relationships with the uncertainty in the input variables. For example, in Figure 5.3, the decision-maker can easily recognise that the probability of undesirable outcomes becomes greater with the increases in the initial investment (the colour on the top row of the grid is more orange at the right). In contrast, the probability of undesirable outcomes becomes lower with the increases in the values of cash inflow (the colour on the second row of the grid is more yellow at the right).

Exploring and analysing the risk of undesirable outcomes under particular scenarios

In addition to the overview of the probability of undesirable outcomes, Risk Explorer allows the decision-maker to focus on particular scenarios (i.e. specific values of input variables) and explore the probability of undesirable outcomes under these scenarios. To focus on a specific scenario, the decision-maker needs to fix the value that represents the scenario. This can be done by clicking on the cell containing the variable's value. As a result, this cell is highlighted, and a new grid is shown. The new grid shows the range of values of other variables and the range of colours in the new grid conveys the new range of the probability of undesirable outcomes. The new range of the probability values is calculated based on fixing the value in the highlighted cell and taking every possible value of the other variables and calculating what proportion of these combinations will result in undesirable outcomes.

Figure 5.4 shows an example of the analysis and exploration of probability of undesirable outcomes based on fixing the initial investment at $90000 (the highlighted cell in the top grid). The lower grid in Figure 5.4 shows the probability of undesirable outcomes associated with the decision alternative under the values of inflow, outflow and rate. By observing the colour variation in the lower grid, the user can be better informed about the combinations of the other input variables that would result in high or low probability of undesirable outcomes. In this way the user can experiment with many different "what-if" scenarios and explore the range of risk values (i.e. probabilities) associated with the other input variables under these scenarios.

Figure 5.4: A new range of colours in the second grid after holding the Init. Investment at $90000

Flexibility in changing the range of values of input variables and number of divisions

For a finer-grained analysis and representation of the uncertainty and probability of undesirable outcomes, the user can change the range of values of input variables and number of divisions. The range of values for each input variable can be modified by changing its minimum and maximum values through the associated text boxes. For example, Figure 5.5 shows the effect of changing the range of inflow from ($25000, $35000) (as displayed in Figure 5.4) to ($20000, $30000). As shown in Figure 5.5, the colours in the upper grid become darker which means that the probability of undesirable outcome is very high for almost all of the values of input variables. However, this does not mean that the probability of undesirable outcomes associated with all possible scenarios is very high. For example, when the decision-maker chooses the value $30000 from inflow (the highlighted cell in the upper grid), he/she can notice from the lower grid that there are some combinations of the other input variables which would have low or no probability of undesirable outcomes.

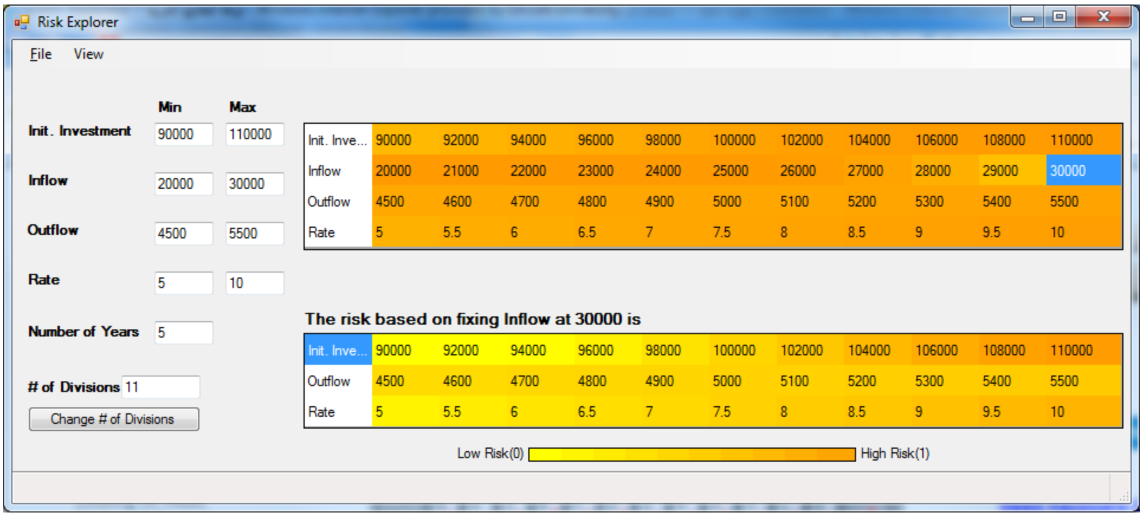


Figure 5.5: The influence of changing the Inflow Range on the calculated risk and the colour range

The decision-maker can also modify the number of scenarios to be investigated by changing the number of divisions for the range of values of input variables. For example, in Figure 5.5, we have divided each input variable into eleven divisions. However, if the decision-maker wants to analyse and explore the probability of undesirable outcomes, for example, under three scenarios, he/she can change the number of divisions (cells) in the grid to three divisions.

5.4 Pilot evaluation of exploratory prototypes

After the design and implementation of the Interactive Tornado Diagram and Risk Explorer, they were evaluated through a controlled experiment (see Appendix A for details). This was a pilot study to investigate whether the visualisation concepts were well understood or not. Ten participants from the Lincoln University community were recruited. They were given a decision-making scenario and a number of questions to answer such as: For the displayed ranges, which variable do you think has the most effect on the risk of making a loss? Approximately, for what range of cash inflow can you be assured that the NPV will stay > 0 i.e. there is no risk of making a loss? If the Inflow is $30000, what is the range of rate values that will ensure no risk of making a loss? While working through the questions, the participants were observed and their feedback about the usefulness of the information provided and suggestions for further improvement were collected.

The participants provided both positive and negative feedback about the information they obtained from each of the exploratory prototypes. Using the interactive tornado diagram, participants were able to explore the effect of uncertainty in the input variables on the outcomes of the decision model. They were also able to compare the effects of uncertainties on outcomes and recognise key uncertain variables. However, most participants found that the information provided by the interactive tornado was not enough to be fully informed about the possible outcomes. They expressed a need for further information related to the likelihood of these outcomes. They also suggested providing information on the entire range of possible outcomes based on varying all input variables within their range of uncertain values.

On the other hand, using the Risk Explorer prototype, the participants were able to recognise the risk (i.e. the probability of undesirable outcomes) associated with the decision alternative and its relationship to uncertainty associated with the values of input variables. They were able to get an overview of the probability of undesirable outcomes by observing the colour variation across the cells in the grids. Also, they could experiment with different scenarios and explore the probability of undesirable outcomes under these scenarios. It was observed that the participants were able to distinguish colours/gradients and link the degree of colour to the probability of undesirable outcomes.

Most participants found that the information about risk (i.e. the probability of undesirable outcomes) provided by Risk Explorer was useful and informative. They were able to explain the rationale of their decisions based on the risk involved in the scenarios. They also showed a higher level of confidence in their decisions compared with the Interactive Tornado Diagram. However, some participants stated that there was a lack of information about the possible outcomes. For example, one participant stated: *"Risk Explorer allows me to see probability of making a loss but it does not inform me about the amount of money I may lose."* This participant suggested that, besides the probability of making a loss, Risk Explorer should provide details about possible outcomes.

Participants provided some useful suggestions for further improvement and refinement of the current prototype of Risk Explorer. Some participants suggested extending Risk Explorer to be amenable to a larger number of decision alternatives and input variables.

For instance, one participant commented*: "I would like to use your application to compare between multiple investments."* Other participants expressed a need to be able to explore the risk associated with the decision making alternatives at several levels of detail. For example, they expressed a need to be able to explore the overall risk associated with a decision alternative based on varying all input variables, as well as the risk associated with the alternative under a smaller and more focused set of scenarios. One participant said: *"Possible modification to Risk Explorer is the possibility of fixing two or more variables, and assessing the risk of making a loss in relation to that selection."*

The suggestions of participants during the pilot evaluation of exploratory prototypes reinforce the design considerations and information requirements discussed in Chapter 4. Generally, decision-making is not only about deciding on whether or not to proceed with one alternative, but it is about choosing a preferred alternative from multiple alternatives or obtaining an order of preferences of these alternatives (Nobre *et al.*, 1999). To achieve these ultimate objectives, decision-makers need to have a complete picture of the key elements of the decision problem. They also require assistance in performing many different tasks such as exploring the pros and cons of alternatives, evaluating and comparing alternatives, and eliminating uninteresting alternatives. All these tasks and others should be taken into account and supported by the InfoVis tool for decision-making support. These exploratory prototypes — the Interactive Tornado Diagram and Risk Explorer — are not sufficiently helpful to support all these tasks. This is because they were mainly designed for "yes/no" decisions; i.e. to decide on whether or not to proceed with an alternative.

5.5 Refinements of exploratory prototypes

Based on the feedback from participants and bearing in mind the information requirements of decision-makers discussed in Section 4.4, a new InfoVis prototype to support informed decision-making under uncertainty and risk (VisIDM) was developed. The amendments to VisIDM addressed three aspects. Firstly, the previous exploratory prototypes were expanded to be able to deal with a larger number of input variables and decision alternatives. Secondly, they were combined to enable the decision-maker to explore and analyse both the possible outcomes of decision alternatives and their associated probabilities. Thirdly, a level that provides overview information of decision alternatives, their possible outcomes, and the overall probability of undesirable outcomes associated with each alternative was added.

The resulting VisIDM prototype is shown in Figure 5.6. The left side of Figure 5.6 shows the Decision Bars which provide overview information on available alternatives, their range of possible outcomes, and the overall probability of undesirable outcomes associated with each alternative. The decision-maker can use this information to choose preferred alternatives from among those available before focusing on particular alternatives for detailed analysis and exploration. The right side of Figure 5.6 shows a refined prototype of Risk Explorer after expanding and combining it with the Interactive Tornado Diagram that was described in Section 5.3.1. This refined prototype of Risk Explorer provides the decision-maker with a detailed view of a particular alternative or several alternatives at the same time with more details on the uncertainty and risk associated with the alternatives under investigation. This detailed information allows the decision-maker to analyse alternatives at several levels of detail and explore the pros and cons of these alternatives under a more focused set of scenarios. The following sections describe the design and interfaces that make up the Decision Bars and Risk Explorer in detail.

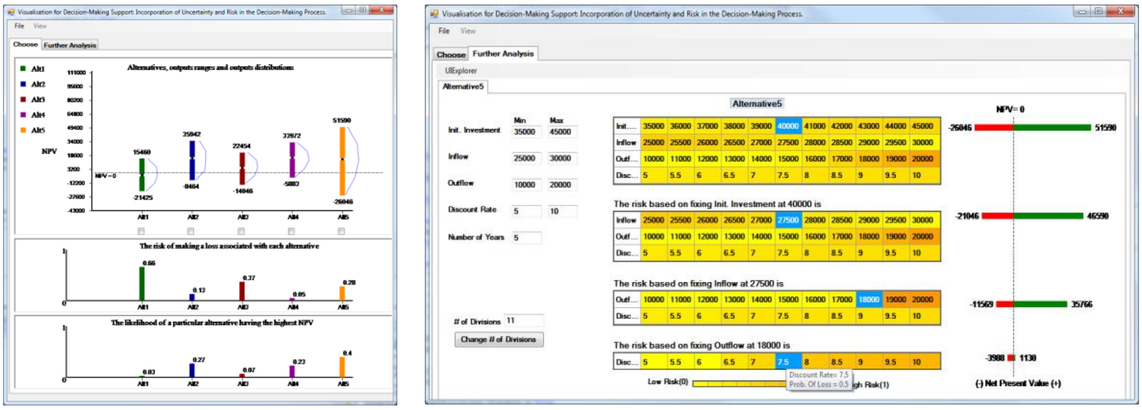


Figure 5.6: the Decision Bars (left) and the Risk Explorer (right)

5.5.1 Decision Bars

As shown in Figure 5.7 from top to bottom, the Decision Bars interface consists of three panels: Outcome, Risk and Likelihood Bars. Each of these panels provides the decision-maker with information about the decision problem at hand and complements the other panels. The following clarify these panels and the information they provide.

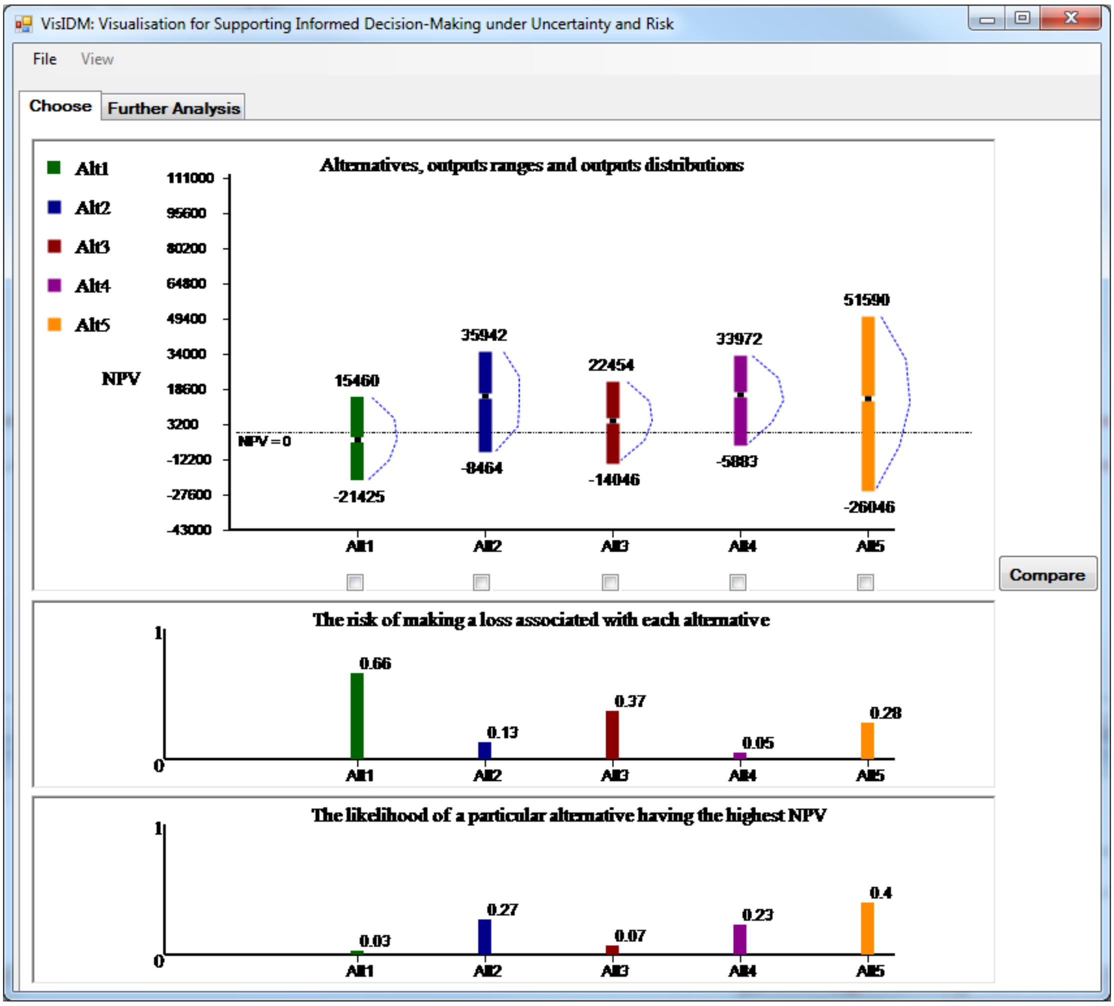


Figure 5.7: Screenshot of Decision Bars interface.

Outcome Bars

The Outcome Bars shown in the top panel of Figure 5.7 present the decision alternatives, each of which is visualised by a bar with a different colour. For instance, the top panel of Figure 5.7 shows that there are five investment alternatives for the decision problem at hand. The length of the bar represents the range of possible outcomes associated with the corresponding alternative (in this case the range of possible NPVs). The black part of each bar represents the mean value of possible outcomes of each alternative. The dashed blue line beside each bar represents the probability distribution of possible outcomes for the corresponding alternative.

The Outcome Bars enable the decision-maker to identify the worst and best possible outcomes for each alternative. For example, in the top panel of Figure 5.7, the decision-maker can identify that alternative 5 has the largest potential gain and also the largest potential loss, by observing and comparing the maximum and minimum possible NPVs of each alternative. Furthermore, the Outcome Bars help the decision-maker to distinguish the proportion of desirable outcomes from undesirable outcomes for each alternative. For example, the Outcome Bars in Figure 5.7 shows that more than half of the NPVs of alternative 1 may result in making a loss (NPV < 0), whereas most of the NPVs for alternative 4 result in making a profit (NPV > 0).

The mean value of possible outcomes (the black part of each bar) gives the decision-maker an idea of which alternative is better in terms of the expected, or mean, value of possible outcomes. For example, the Outcome Bars in Figure 5.7 shows that both alternatives 2 and 4 have the highest expected (or mean) value whereas alternative 1 has the lowest expected value of possible outcomes. The probability distribution of possible outcomes (the dashed blue line) enables decision-makers to identify the relative likelihood of occurrence of the possible outcomes. For example, the dashed blue line of alternative 4 is skewed to the top showing that the outcomes with a higher NPV are more likely.

Risk Bars

The Risk Bars shown in the middle panel of Figure 5.7 provide information on the overall probability of obtaining undesirable outcomes (in this case, the probability of obtaining negative values of NPV). The overall probability of undesirable outcomes associated with each alternative is shown as a vertical bar. The height of the bar represents the probability of undesirable outcomes associated with the corresponding alternative. The higher the bar, the higher the probability of obtaining undesirable outcomes. For example, the middle panel in Figure 5.7 shows that among all possible outcomes for alternative 4 about 5% will result in a loss compared to about 13% for alternative 2.

Unlike Outcome Bars that present the risk as a probability distribution, the Risk Bars present the overall risk associated with each alternative more directly. Consequently, the decision-maker can gain an understanding of the probability of undesirable outcomes associated with each alternative with less effort compared to the effort needed to identify the probability of undesirable outcomes using the Outcome Bars. The decision-maker can then utilise the information about the probability of undesirable outcomes to evaluate, compare and then choose preferred alternatives based on the level of risk he/she is willing to accept.

Likelihood Bars

The Likelihood Bars provide information on the likelihood of a particular alternative having the highest outcome. In other words, these bars show the percentage of outcomes of a particular alternative that are better than all outcomes of other alternatives. The higher the bar, the higher the percentage. For example, the bottom panel of Figure 5.7 shows that about 40% of the outcomes (NPVs) of alternative 5 are higher than all outcomes (NPVs) of other alternatives.

The Likelihood Bars provide the decision-maker with more insight into the effect of uncertainty on the ranking of decision alternatives. For example, consider the Outcome Bars shown in the top panel of Figure 5.7. These bars illustrate that there is overlap between alternatives due to the uncertainty associated with the outcomes of each alternative. This overlap causes a difficulty in ranking the decision alternatives. By calculating the probability of a particular alternative being better than all other alternatives, the decision-maker can be better informed about the ranking of alternatives and the effect of uncertainty on this ranking. For example, the Outcome Bars of alternative 3 and 4 shown in the top panel of Figure 5.7 indicate that there is overlap between their outcomes. The Likelihood Bars show that 23% of outcomes of alternative 4 are better (or higher) than those of any other alternative.

5.5.2 Refined Risk Explorer

This part of VisIDM is an extension and refinement of the previous Risk Explorer that was described in Section 5.3.2. Figure 5.8 shows a screenshot of the refined prototype of Risk Explorer. It adds to the other parts of VisIDM a visualisation tool for exploring and analysing available alternatives either consecutively or simultaneously. This can be done through two ways of interaction with VisIDM: either by clicking the outcome bar related to the alternative intended to be explored and analysed or by ticking the checkboxes corresponding to alternatives and then clicking on the “Compare” button (see Figure 5.7). Both ways of interacting with VisIDM move the decision-maker from the Decision Bars interface to the Risk Explorer interface.

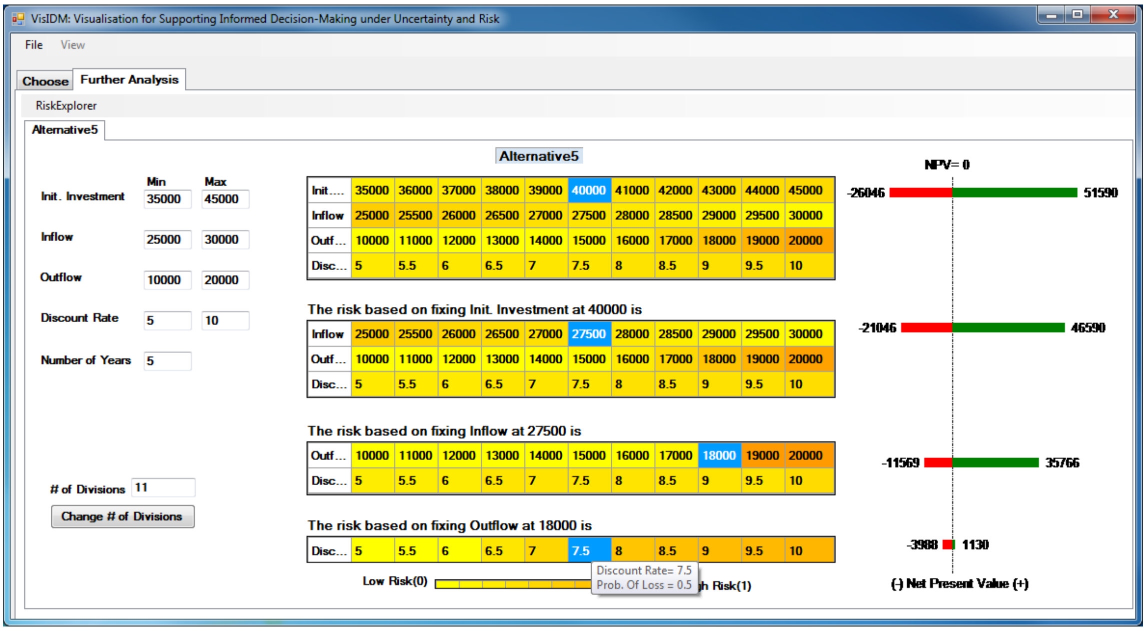


Figure 5.8: A screen shot of Risk Explorer

In the refined prototype of Risk Explorer, the Interactive Tornado Diagram and the previous prototype of Risk Explorer are combined and expanded so that the decision-maker can explore both the possible outcomes and their associated probabilities. The Interactive Tornado Diagram (refer to Section 5.3.1) was modified to use the red/green bars shown in Figure 5.8 (right). The red/green bars still display the effect of uncertainty in the input variables on the possible outcomes of an alternative. The previous prototype of Risk Explorer (refer to Section 5.3.2) was refined to display multiple decision alternatives so that the decision-maker can analyse and explore these alternatives either consecutively or concurrently. In addition, it was modified so that the decision-maker can investigate the probability of undesirable outcomes under several levels of detail based on a more focused set of scenarios. These enhancements are further described in the next sections.

Analysis and exploration of multiple alternatives

Figure 5.9 shows a screenshot of the Risk Explorer prototype after selecting alternatives 1 and 2 for further analysis and exploration. By observing the colour variation across the grid cells, the decision-maker can quickly and easily get an overview of the probability of undesirable outcomes associated with each alternative. The decision-maker can then use this overview to compare between alternatives in terms of the risk involved in each alternative before focusing on a specific set of scenarios. For example, as shown in Figure 5.9, when comparing alternatives 1 and 2, the decision-maker can recognise that the probability of making a loss associated with alternative 1 is much higher than that associated with alternative 2; the colour of many cells in the grid of alternative 1 is much darker than that of alternative 2. The same overview information can also be obtained from the Decision Bars interface. However, Risk Explorer provides more detail about the factors that form the probability of undesirable outcomes associated with the decision alternative.

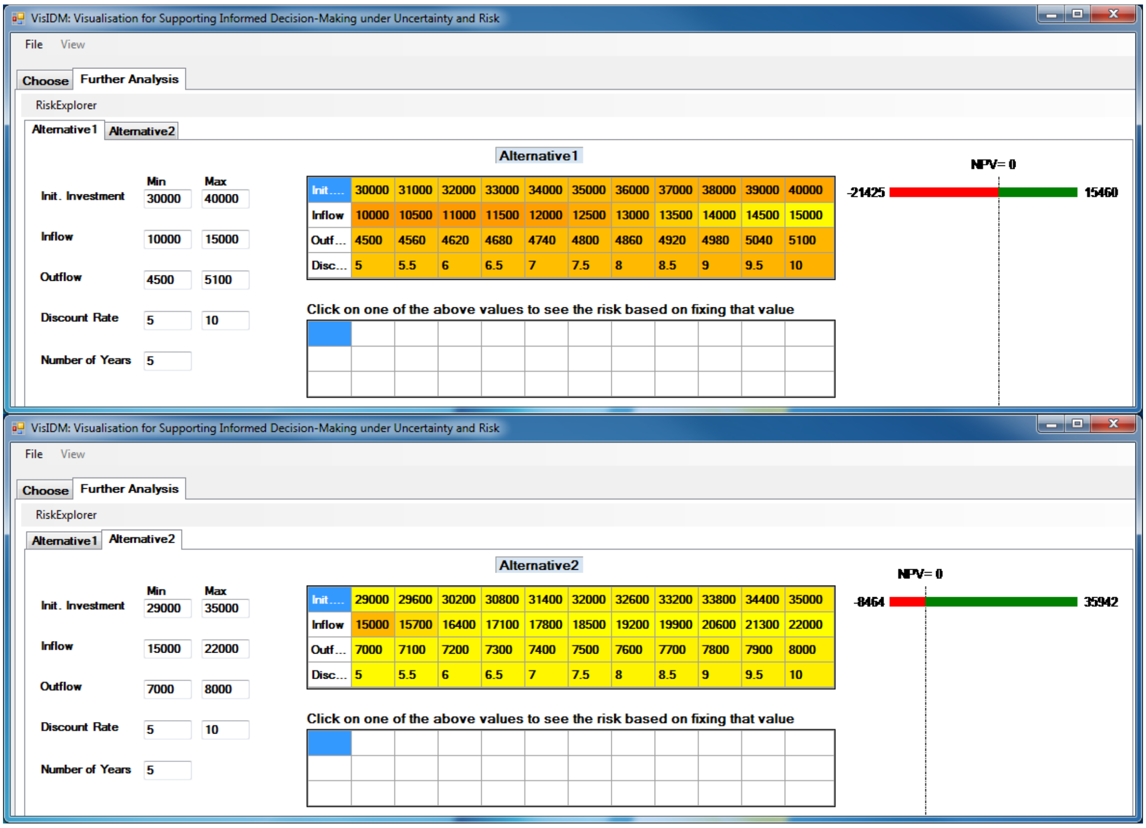


Figure 5.9: A screenshot of Risk Explorer after selecting alternatives 1 and 2 for further exploration and comparison

Risk Explorer also displays the range of possible outcomes resulting from uncertainty in the input variables as horizontal red/green bars. The horizontal red/green bar provides overview information on the range of possible outcomes which is calculated by allowing all input variables to vary within their ranges of values and calculating all possible combinations of these values. The horizontal red/green bar informs the decision-maker about the maximum and minimum potential outcomes under all possible scenarios (i.e. all possible combinations of the variables values). In addition, by observing the red part of the bar, the decision-maker can identify the proportion of undesirable outcomes (e.g. the negative NPVs that will make a loss as in the example shown in Figure 5.9). Conversely, he/she can identify the proportion of desirable outcomes (in this case the positive NPVs that will make a profit) by observing the green part of the bar.

Analysis and comparison of alternatives under more focused set of scenarios

Figure 5.10 shows an example of exploring and analysing alternatives 2 and 5 under specific scenarios based on fixing two input variables initial investment at $35000 and discount rate at (10%). As shown in Figure 5.10, the two chosen cells are highlighted and a new grid is shown for each alternative. The new grid shows the range of values of other input variables (i.e. the inflow and outflow) and the range of colours in the new grid conveys the new range of probability of undesirable outcomes associated with the values of other variables for each alternative. In addition to the resulting grid, a new red/green bar is shown to the right of the grid for each alternative. The red/green bar shows the range of possible outcomes resulting from fixing the variables' values in the highlighted cells while varying the other variables within their ranges of values.

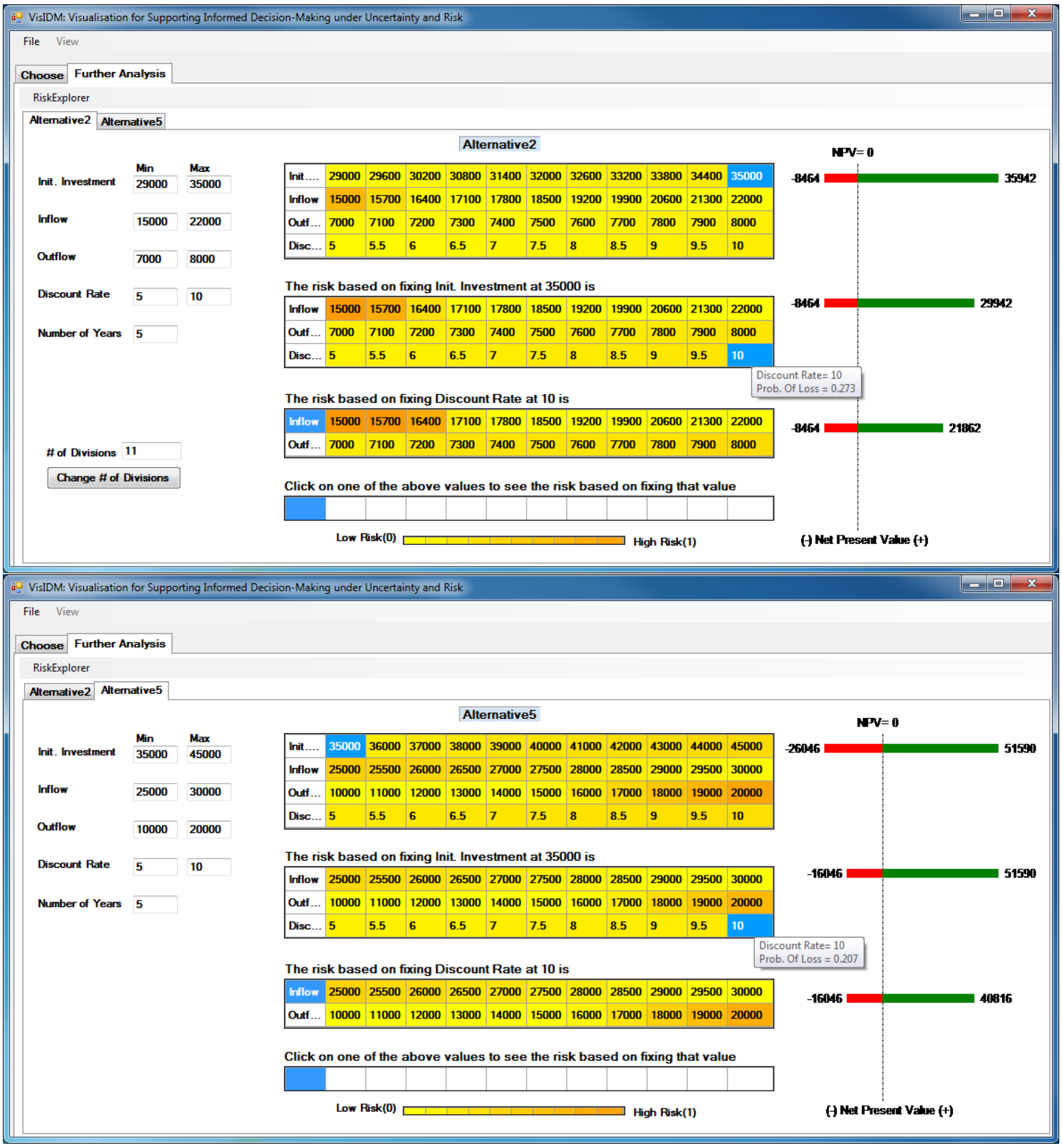


Figure 5.10: A screenshot of Risk Explorer after exploring alternatives 2 and 5 under initial investment of \$35000 and discount rate of 10%

Based on the resulting grids and red/green bars, the decision-maker can evaluate and compare between alternatives in terms of the probability of undesirable outcomes and range of possible outcomes under the selected scenarios. For example, the new grids and red/green bars in Figure 5.10 show that if the two input variables initial investment and discount rate are fixed at \$35000 and 10% respectively, then about (27%) of NPVs of alternative 2 will result in a loss compared to about 20% for alternative 5 (see the popup windows shown in Figure 5.10). Conversely, according to the red/green bars, the maximum loss and profit potential associated with alternative 5 (-\$16046, \$40816 respectively) are greater than those associated with alternative 2 (-$8464, $21862 respectively).

Two ways of identifying the risk (i.e. the probability of undesirable outcomes)

The decision-maker can follow two ways of interacting with the Risk Explorer interface in order to identify the probability of undesirable outcomes associated with an alternative. One way is by observing the colour variation across the cells in the resulting grids. By comparing the range of colours in the grids corresponding to each alternative, the decision-maker can identify the probability distribution of undesirable outcomes and compare alternatives in terms of the risk magnitude. For example, Figure 5.11 shows that under a discount rate of 10% the probability of making a loss associated with alternative 1 is higher than that associated with alternative 2 according to the colour variation across the cells.

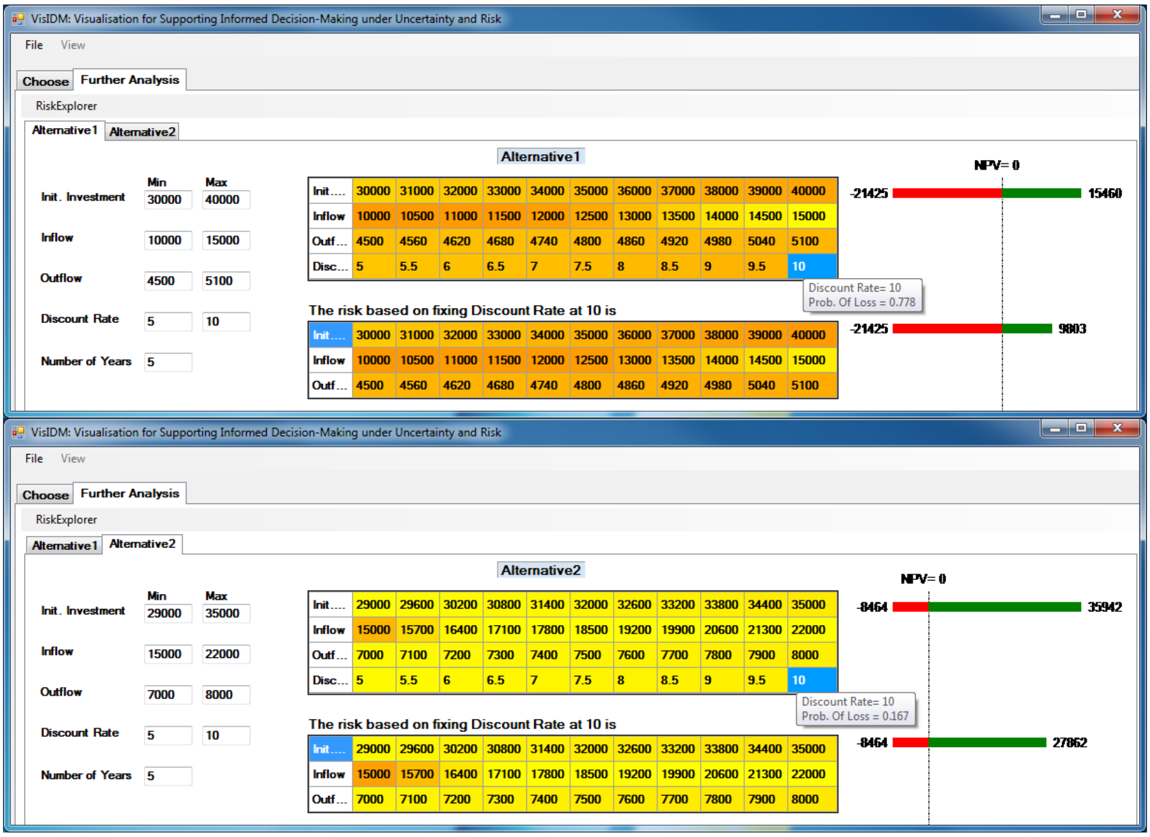


Figure 5.11: A screenshot of Risk Explorer displaying the selected alternatives 1 and 2

In many scenarios, the decision-maker could be unable to identify the probability of undesirable outcomes using the colour variation across the cells; particularly, when the scenarios had similar risk profiles (see Figure 5.10 for an example). In this situation, instead of using colour variation across the cells to identify the probability of undesirable outcomes, the user can retrieve the numerical value of the probability by hovering over the cells. For example, the popup windows in Figure 5.11 shows that if the discount rate is fixed at 10% (the highlighted cell in the top grid of each alternative) while allowing the other variables to vary within their ranges of values about 78% will result in a loss in alternative 1 compared to about 17% in alternative 2.

5.6 Implementation

The proposed prototypes were implemented using Visual Basic .NET 2008 and GDI+. GDI+ is a class-based application programming interface (API) used in Microsoft .NET Framework for graphics programming. Visual Studio provides several components and methods to deal with the grid view that can be customised down to the cell level. For example, it provides flexibility to add and remove rows and columns from a grid view, making the grid view amenable to any number of input variables and scenarios. In addition, the flexibility in customising the colours of the cells in the grid facilitated the use of colours to represent the numerical values of risk. This flexibility in customising the colours was also useful for highlighting and keeping track of cells and scenarios under investigation.

Figure 5.12 shows the architecture of implementation of VisIDM. The implementation of VisIDM is composed of two main components: the Visualisation and Model. The Visualisation component contains methods for rendering the visual elements of VisIDM and interacting with the user. It is also responsible for presenting the control panel that allows the user to provide his or her estimates of uncertainties for the input variables. The Model component contains methods for generating model outcomes, risk values (i.e. probability of undesirable outcomes) and possible scenarios.

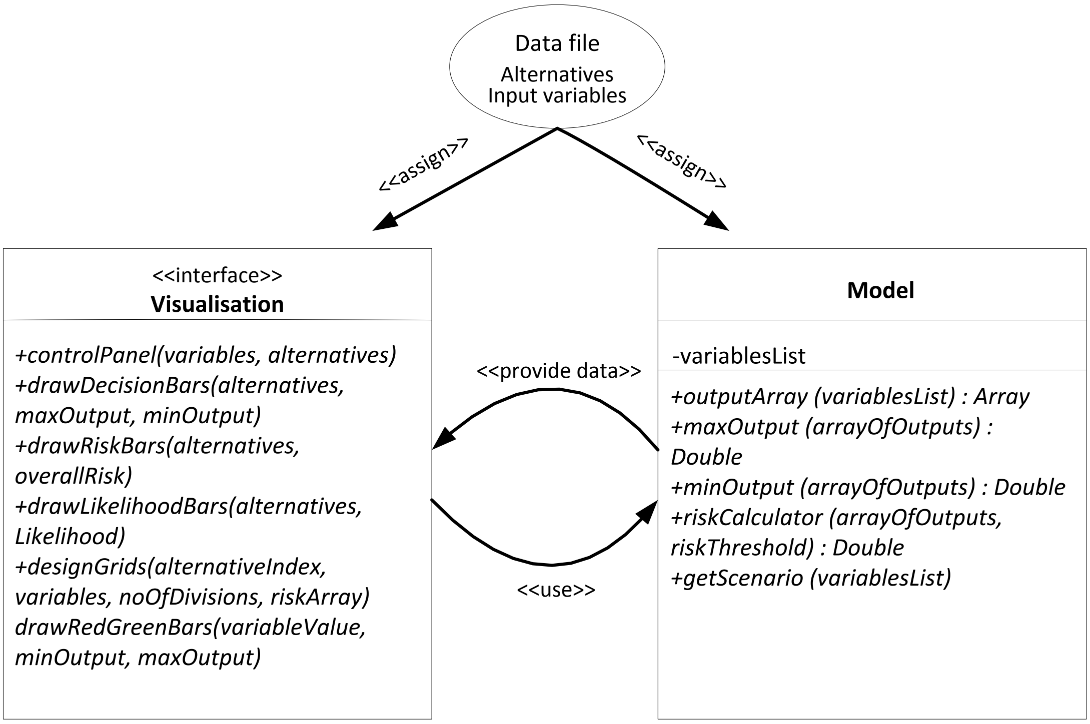


Figure 5.12: Architecture of implementation of VisIDM

The dataset used for the visualisation comes from two sources. The first source is the Data file which contains data on the available alternatives, input variables and range of values for each of the input variables (see Appendix B for details). This file is loaded into VisIDM and assigned to the Visualisation and Model Components. The second source of data comes from the Model component which is responsible for generating the outcomes and risk values (i.e. probability of undesirable outcomes) for each available alternative based on the model and risk calculator used.

As shown in Figure 5.12, the implementation of the Visualisation component is separated from the Model component. This decomposition allows for convenient extension of VisIDM to support the needs of other models and input variables.

5.7 Summary and discussion

Through an iterative process of design, evaluation and implementation, VisIDM was developed. In a relatively early stage of the design process, two exploratory prototypes, the Interactive Tornado Diagram and Risk Explorer, were designed. Both were primarily intended to facilitate the integration of uncertainty into the decision-making process and expose its effect on outcomes and risk associated with decision-making.

The exploratory prototypes were then evaluated in order to collect feedback from participants on the information provided and suggestions for further improvement. Using the interactive tornado diagram, most participants found that the information on the effect of uncertainty in the input variables on possible outcomes was insufficient for them to feel informed about the outcomes. On the other hand, using Risk Explorer, most participants found that the information about the risk (i.e. the probability of undesirable outcomes) provided by Risk Explorer was useful and informative.

Based on the feedback and suggestions of participants, reinforced by the design considerations and information requirements of decision-makers discussed in Chapter 4, the prototype of VisIDM was developed. VisIDM consists of two main parts: the Decision Bars and Risk Explorer. Decision Bars provide overview information of the decision problem under uncertainty and risk. The Decision Bars interface consists of three panels: the Outcome, Risk, and Likelihood Bars. Outcome Bars provided information on decision alternatives, their range of possible outcomes, and the probability distribution of possible outcomes. Risk Bars provided information on the overall probability of obtaining undesirable outcomes associated with each alternative. Likelihood Bars provides information on the likelihood of a particular alternative having the highest outcome. Using all these bars, decision-makers can compare and then choose preferred alternatives based on the risk/outcomes profile of each alternative. The Risk Explorer prototype provides decision-makers with a multivariate representation of uncertainty and risk associated with the decision alternatives. It also facilitates the interactive analysis and comparison of available alternatives, either consecutively or simultaneously, at different levels of detail.

The VisIDM prototype is ultimately expected to support making informed decisions under uncertainty and risk. Also, it aims to raise the awareness of decision-makers about the uncertainty and risk involved in the decision problem. However, the question of whether VisIDM is actually helpful to the target end users requires conducting an evaluation study, which will be discussed in Chapter 6.

CHAPTER 6
EVALUATION STUDY

6.1 Introduction

This chapter presents a study conducted to assess the ability and usefulness of the VisIDM prototype for assisting people to make informed decisions under uncertainty and risk. As discussed in the previous chapter, the VisIDM prototype consists of two main parts: the Decision Bars and Risk Explorer. Decision Bars provide decision-makers with an overview of available alternatives through three panels: Outcome, Risk, and Likelihood Bars. In contrast, Risk Explorer provides a detailed view of the uncertainty and risk associated with each of the decision alternatives and facilitates the analysis and comparison of these alternatives in more detail.

To explore the effect of all the components of VisIDM on informed decision-making under uncertainty and risk, a study that utilised a qualitative approach was designed and conducted. The purpose and methodology of this study are described in this chapter, whereas the results obtained are presented and discussed in the next two chapters.

6.2 Purpose

The main purpose of this study was to answer the research question of this thesis, which was presented in Section 1.2 as follows:

How can InfoVis tools assist people in making informed decisions under uncertainty and risk?

While the ability and usefulness of VisIDM for assisting people to make informed decisions under uncertainty and risk were assessed, the focus was also placed on: 1) exploring how participants utilised the given interactions and visual presentations of information of VisIDM to arrive at their final decisions; 2) exploring the types of information used by participants to inform and justify their decisions; and 3) exploring how VisIDM affected participants’ understanding and interpretation of information presented.

6.3 Method

Owing to the exploratory nature of the study objectives, a qualitative approach to data collection and analysis was adopted. To ensure the validity of the results, the study used a triangulation by combining different data collection methods (Creswell, 1998). Data was collected using semi-structured interviews with participants, observations of participants (aided by the think-aloud protocol) and content analysis of participants' written responses and answers of open-ended questions. The trials were conducted until our analysis reached a saturation point; where the addition of further participants did not lead to new results (Denzin & Lincoln, 2005; Patton, 2005).

The interviews and observations during the trials were audio recoded and transcribed for analysis. Data was coded and then analysed using qualitative content analysis. The qualitative content analysis is a method of analysing narrative or verbal data to identify prominent themes and patterns (Hsieh & Shannon, 2005). It is a method used for making replicable and valid inferences from data with the purpose of providing knowledge, new insight and a description of phenomena (Elo & Kyngäs, 2008). An advantage of the qualitative content analysis is that large volume of textual data can be dealt with and used in supporting evidence.

There are two main reasons a qualitative approach was considered for addressing the study objectives. Firstly, the study did not focus on the decision outcomes to measure how informed the decision was, but rather on the process of decision-making, that is, the tasks performed and types of information used by participants to arrive at their final decisions. The qualitative approach to evaluation implies essentially an emphasis on the processes and interactions rather than measurements, such as accuracy, time to completion, or satisfaction, as required in quantitative approaches. Secondly, the study aimed to explore how VisIDM affected participants' perception and interpretation of information presented. The verbal protocols used for this study provided participants the opportunity to talk about the information and experiences that affected their perception and understanding of the decision problem without placing priori limitations, assumptions, or categories on their responses.

The VisIDM prototype was divided into three interfaces: Outcome bars, Risk and Likelihood Bars, and Risk Explorer (refer to Section 5.5 for detailed description of these interfaces). The participants were firstly presented with the Outcome Bars interface.

Then, they were presented with the Risk and Likelihood Bars interface. Lastly, they were presented with the Risk Explorer interface. The intention of dividing VisIDM into three interfaces was to find out which information the participants were genuinely interested in and to explore how the information was used in decision-making. The idea of dividing VisIDM into three interfaces was inspired by a similar, but more systematic, methodology proposed by Huber *et al.* (1997), called Active Information Search (AIS) method. The AIS method presents participants with an overview description rather than complete and detailed information of the decision problem. Then, it asks participants about what additional information they need to be better informed.

6.3.1 Participants

The study was conducted with a total of 12 participants. The number of participants was not predetermined before the initiation of the study, but rather was determined by reaching a saturation point. Recruitment ceased when the information being collected became repetitive across participants and further information and analysis no longer yielded new variations. All participants were postgraduate students from different departments in the Faculty of Commerce at Lincoln University (2 females and 10 males). One of the participants was also working as a lecturer in the Department of Farm Management and Agribusiness. The participants were recruited through email broadcasts to students of the Faculty of Commerce. In addition, some responded to recruitment fliers placed in and around the university campus.

Although there are methodological arguments against recruiting students as a sample representative of the target end users (Gordon *et al.*, 1986), other researchers have countered these arguments (Greenberg, 1987). In this study, it was considered that the students should represent a random sample of potential users. This was motivated by their varying level of experience in using financial information and models in analysing and interpreting data related to business activities. Furthermore, the participating students had varying levels of experience in decision-making especially under uncertainty and risk. This experience varied from being novices to being employed in professional positions where they were using financial information and models to assist in decision-making under uncertainty and risk on a regular basis.

Figure 6.1 shows the level of experience of participants in the three areas of financial information and models, decision-making under certainty, and decision-making under uncertainty and risk. The participants subjectively classified their experiences into one of three experience levels using a three point scale, which were described as: (1) novice (never used financial information in decision-making), (2) intermediate (basic understanding of financial information and decision-making concepts), and (3) expert (regularly uses financial information and models in decision-making and analysis).

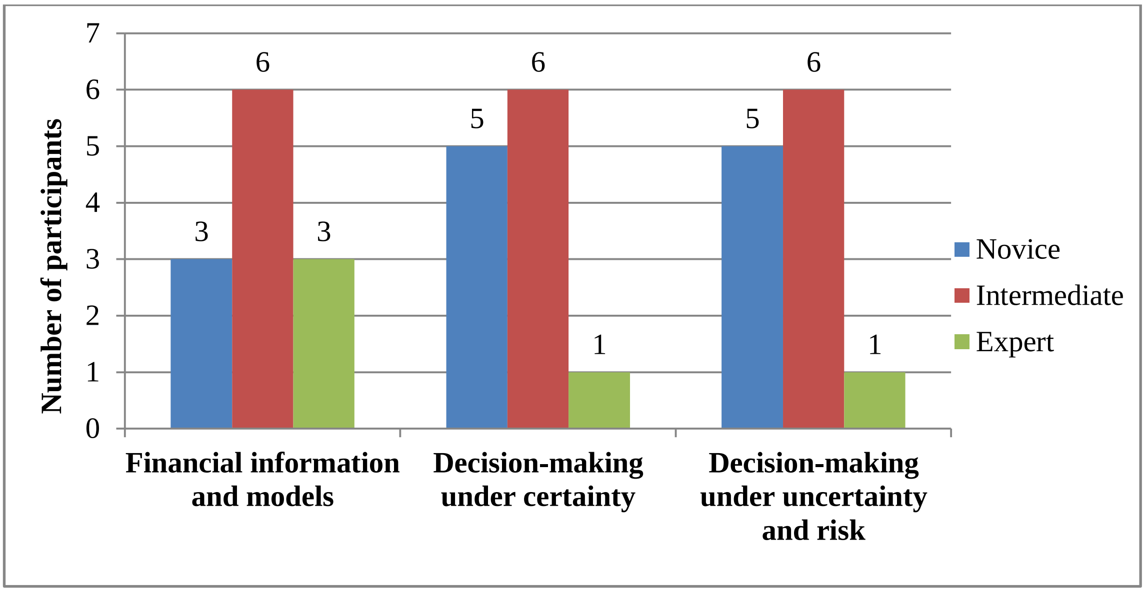


Figure 6.1: The participants' level of experience in financial information and models, decision-making under certainty, and decision-making under uncertainty and risk

6.3.2 Evaluation setup

The study was setup in a lab-based environment. A case study of an investment decision-making problem under uncertainty and risk that was relevant to the knowledge and experience of the participants was utilised in this study. The decision problem consisted of five investment alternatives. The data was prepared so that each investment alternative had a different risk/profit profile. Some investment alternatives lead to a low profit and low risk of making a loss, while others had a high profit and high risk of making a loss. For all alternatives, we used the same input variables to evaluate their risk/profit profiles. The input variables were assigned different ranges of uncertain values. To make sure that all alternatives were assessed on the same basis, the participants were not allowed to control or change the range of uncertain values for any of the input variables. The data used in this study is provided in Appendix B.

Because all alternatives involved the investment of dollars, the Net Present Value (NPV) model was used for evaluating and comparing the profitability of alternatives. As described in Section 5.2, NPV estimates the extent to which the profits of an investment exceed its costs. A positive NPV indicates that the investment is profitable, while a negative NPV indicates that the investment is making a loss. Due to the presence of uncertainty in the values of input variables of the NPV model, each alternative can lead to many possible outcomes (i.e. NPV values) and a varying probability of making a loss.

We put participants in the situation of making decisions taking into account the uncertainty and risk associated with each alternative. The following scenario was given to participants: "*Suppose you are planning to make an investment and you have five alternatives to choose from: Alt1, Alt2, Alt3, Alt4 and Alt5. Because they all involve the investment of dollars, you are using the Net Present Value (NPV) model as a basis for the evaluation of alternatives. You are uncertain about the exact values of the NPV's input variables. Therefore, there is a probability of making a loss associated with your decision. Your objective here is to determine which alternative would be chosen in the presence of uncertainty and risk.*"

6.3.3 Measures of informed decision-making

A number of measures of informed decision-making were used in this study (refer to Section 2.5). These included: the level of confidence that the participants had made informed decisions and the adequacy of information to make informed decisions. However, these measures focus on the decision outcomes; i.e. they can be collected only after making a decision. Hence, they do not reflect the multidimensional nature implicit in the definition of informed decision-making (Marteau et al., 2001). As discussed in Section 2.5, most definitions of informed decision-making comprise two main dimensions: the decision outcomes and the process of decision-making. Therefore, in addition to the aforementioned measures, the decision-making processes; that is, the tasks carried out and types of information used by participants were evaluated and analysed. To explore the tasks performed and information used by participants, a number of process-tracking techniques were used (Bekker et al., 1999). These are the verbal protocol of the thinking aloud technique; tape-recorded conversations; and notes taken during the observations.

6.3.4 Procedure

The participants followed the procedure summarised in Table 6.1. A more detailed description of each step is in Appendix B.

Table 6.1: Procedure of the evaluation study

Seq.	Step	Description
1	Introduction	All participants were introduced to the objectives of the study and a brief description of its procedure.
2	Consent Form	All participants were given a consent form to read and sign as part of the Lincoln University Human Ethics Committee procedure (a copy of the ethics approval is in Appendix B).
3	Background questionnaire	All participants were asked to rate their level of experience in three areas: (1) the use of financial information and models to analyse business activities, (2) decision-making under certainty, and (3) decision-making under uncertainty and risk.
4	Tutorial	All participants were given a tutorial on detailed features of the VisIDM prototype and the three interfaces used in the study.
5	Practice phase	All participants were given a set of tasks to familiarise themselves with the three interfaces of VisIDM used in the study.
6	Test phase	All participants were presented with the decision-making scenario used in the study (refer to Section 6.3.2). Then, they were asked a number of open-ended questions where they had to make decisions taking into consideration the uncertainty and risk associated with each alternative.

6.3.5 Tasks

Practice phase

During the practice phase, the participants were given a set of tasks pertaining to decision-making under uncertainty and risk (see Appendix B for details). The practice tasks varied in their difficulty from primitive low-level tasks such as locate or identify a value to higher-level tasks that required a combination of primitive tasks to be executed (e.g. identify trends and discover relationships). The participants were required to interact with and use information provided by each visualisation interface in order to complete the practice tasks correctly.

In the Outcome Bars interface shown in Figure 6.2, the participants were given the following tasks as listed in Table 6.2.

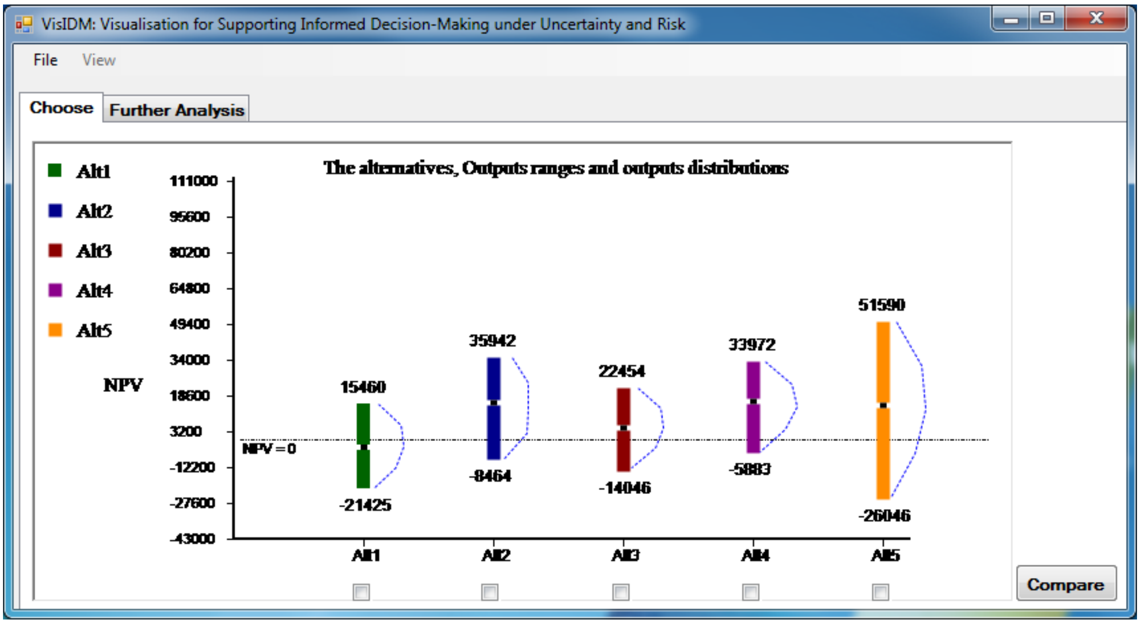


Figure 6.2: A screenshot of the Outcome Bars interface

Table 6.2: The practice tasks that were given to participats in the interface of Outcomes Bars

No.	Task/Question Formulation	Purpose
1	Which alternative has the greatest range of NPV values?	Identify and expose uncertainty
2	Which alternative has the maximum possible NPV?	Identify and find extremum
3	Which alternative has the minimum possible NPV?	Identify and find extremum
4	For Alt4 most of the possible values of NPV are?	Locate and extract pattern from the distributions of outcomes
5	What are the top two alternatives according to the mean value of NPV values?	Identify and compare the mean values of outcomes

In the Risk and Likelihood Bars interface shown in Figure 6.3, the participants were given the following practice tasks as listed in Table 6.3.

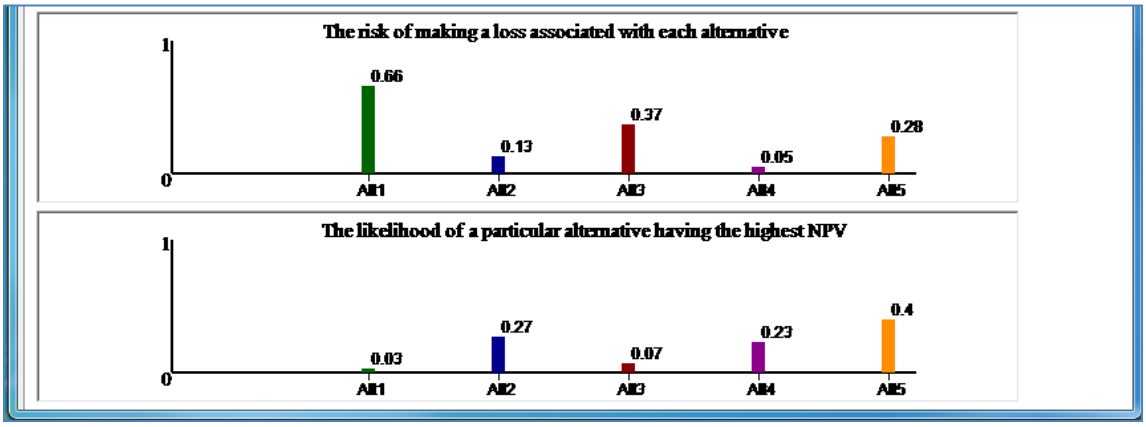


Figure 6.3: A screenshot of the Risk and Likelihood Bars interface

Table 6.3: The practice tasks given to participants in the interface of Risk and Likelihood Bars

No.	Task/Question Formulation	Purpose
1	How much higher is the risk of making a loss for Alt5 compared to Alt2?	Identify and compare between alternatives in terms of the risk
2	What are the two most risky alternatives (i.e., alternatives that involve highest probabilities of NPV being less than zero)?	Compare and rank alternatives in terms of the risk
3	How often would you expect Alt2 to have the highest return (i.e. highest NPV)?	Find out the likelihood of an alternative having the highest outcomes
4	What are the two alternatives that have the greatest likelihood of having the highest NPV?	Compare and rank alternatives in terms of the likelihood that each alternative having the highest outcomes.

In the Risk explorer interface shown in Figure 6.4, the participants were given the following practice tasks as listed in Table 6.4.

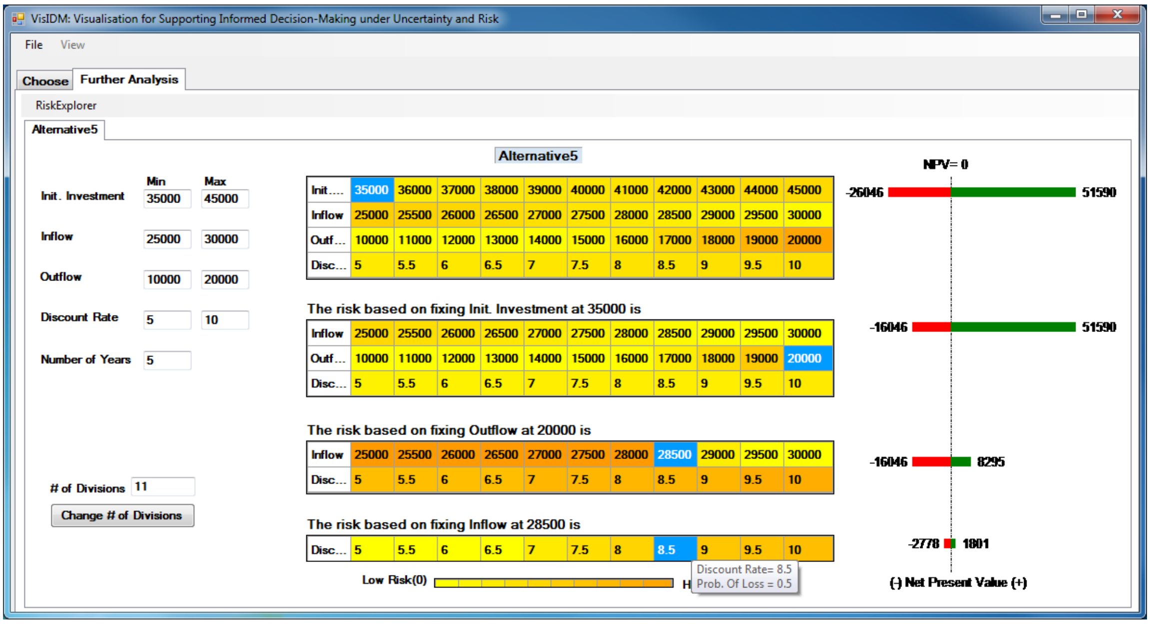


Figure 6.4: A screenshot of the Risk Explorer interface after selecting one alternative for further analysis and exploration

Table 6.4: The practice tasks given to participants in the interface of Risk Explorer

No.	Task/ Question Formulation	Purpose
1	Based on the displayed ranges of input variables, which variable do you think has the most effect on the risk of making a loss?	Identify trends, discover relationships, and concretize relationships
2	Based on the displayed ranges of NPV values (the red/green bars), approximately what proportion of the possible NPV values will make a loss?	Determine proportions
3	For what range of Cash Outflow values can you be assured that the NPV will stay>0 i.e. there is no risk of making a loss? (Other input variables can vary within their ranges).	Determine parameters values and concretize relationships
4	Suppose that you have decided to make an Initial Investment of $35000, at what range of cash Inflow values can you be sure that the NPV will stay > 0 i.e. there is no risk of making a loss?	Expose uncertainty, concretize relationships, and formulate cause and effects

5	Suppose that the Cash Inflows are expected to be $30000 each year, from the bottom red/green bar approximately what proportion of the possible NPV values will make a loss?	Determine proportions, expose uncertainty, concretize relationships, and formulate cause and effects
6	Suppose you fixed the Initial Investment at $45000, Cash Inflow at $25000, and Cash Outflow at $14000, what is the range of Discount Rate that leads to a risk of making a loss less than or equal to 0.2?	Determine parameter values, formulate cause and effects, concretize relationships, and multivariate explanation

The practice tasks were inspired by a set of rules for decision-making under uncertainty and risk. As discussed in Section 2.4.2, the literature on decision-making provides many rules that describe how decisions should be made under uncertainty and risk. These include: Wald's maximin rule, Savage's minimax rule, Hurwicz's maximax rule, and the Laplace insufficient reason rule. For example, in the Outcome Bars interface, the participants were asked to identify the decision alternative that has the maximum potential outcome. Identifying the maximum outcome is one of the basic tasks used in the Hurwicz's maximax rule.

The practice tasks were also inspired by a prominent study in the field of information visualisation by Amar & Stasko (2005). They propose a set of high-level knowledge tasks for the design and evaluation of information visualisation to support decision-making under uncertainty. These tasks include exposing uncertainty, concretising relationships, formulating cause and effect, determining domain parameters, determining multivariate explanations, and confirming hypotheses (refer to Section 3.3.1 for further description of these tasks).

Test phase

During the test phase, the participants were asked a number of open-ended questions where they had to make decisions and explain how they used the information provided to arrive at their decisions. The following questions were repeated for each of the three interfaces of VisIDM used in the study:

- *What do you think are the best two alternatives?* (Ranking problem)

- *From among your best two alternatives, which alternative do you prefer the most? What factors would influence your choice between these two?* (Choice problem)

The above questions were designed to be consistent with the ultimate objectives of decision-making. As discussed in Section 2.2, decision-makers are generally interested in either choosing one alternative (a choice problem) or obtaining an order of preferences of the alternatives (a ranking problem) (Nobre *et al.*, 1999; Saaty, 1994). To achieve these ultimate objectives, the participants had to utilise different types of information provided by each visualisation interface and perform several operations.

After completing the above questions, the participants were asked to rate their level of confidence that they had made informed decisions using each of the three interfaces. A five point scale was used to measure each participant's level of confidence, where 1 = "not confident at all", and 5 = "very confident."

At the end of the test phase of each interface, the participants were asked to assess whether the information provided was adequate for making informed decisions. The following question was repeated for each interface:

- *Do you feel that you have enough information to make an informed decision? If not then how could this be solved so that you feel better informed?*

The purpose of this question was to collect feedback from participants about the types of information they might need to be able to make better informed decisions. This question provided important feedback related to the gap between what is being shown by these visualisation interfaces and what actually needs to be shown to draw a conclusion for making informed decisions under uncertainty and risk (Amar & Stasko, 2005).

CHAPTER 7
RESULTS

7.1 Introduction

This chapter presents the results obtained from the study described in the previous chapter and discusses in detail how they were arrived at. It also summarises the main findings and their potential implications on informed decision-making under uncertainty and risk.

As described in the previous chapter, the study was designed to explore the ability and usefulness of VisIDM for assisting people to make informed decisions under uncertainty and risk. It also focused on exploring and understanding how VisIDM was used by participants and what features supported their exploration and perception of information. To be consistent with the study objectives (refer to Section 6.2), the results were grouped into the following main categories:

1. Decision-making processes; i.e., the sequence of operations pursued and information used by participants to arrive at their most preferred alternatives using each of the three interfaces of VisIDM.

2. The participants' level of confidence that they had made informed decisions using each of the three interfaces of VisIDM.

3. Adequacy of information to make informed decisions using each of the three interfaces of VisIDM.

7.2 Sequence of operations pursued by participants using the Outcome Bars interface

The content analysis of the results showed that the participants performed several operations to arrive at the final ranking of their two preferred alternatives and to choose the most preferred one. However, they relied on different types and amounts of information to accomplish these operations. Figure 7.1 shows the sequence of operations pursued by participants while using the Outcome Bars interface shown in Figure 7.2. Table 7.1 lists the types of information obtained and used by participants to perform these operations and their frequency of use.

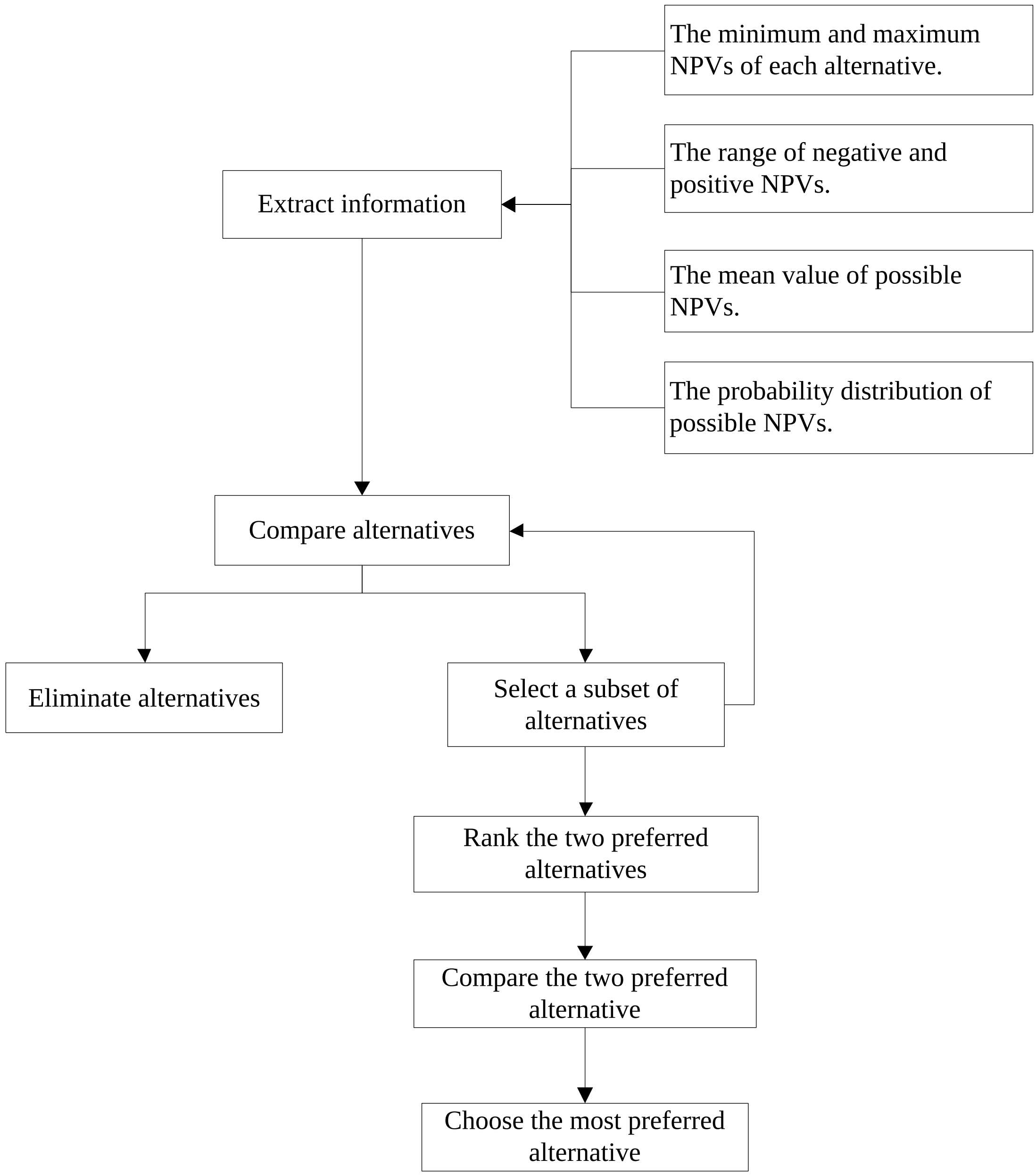


Figure 7.1: The sequence of operations performed by participants while using the Outcome Bars interface.

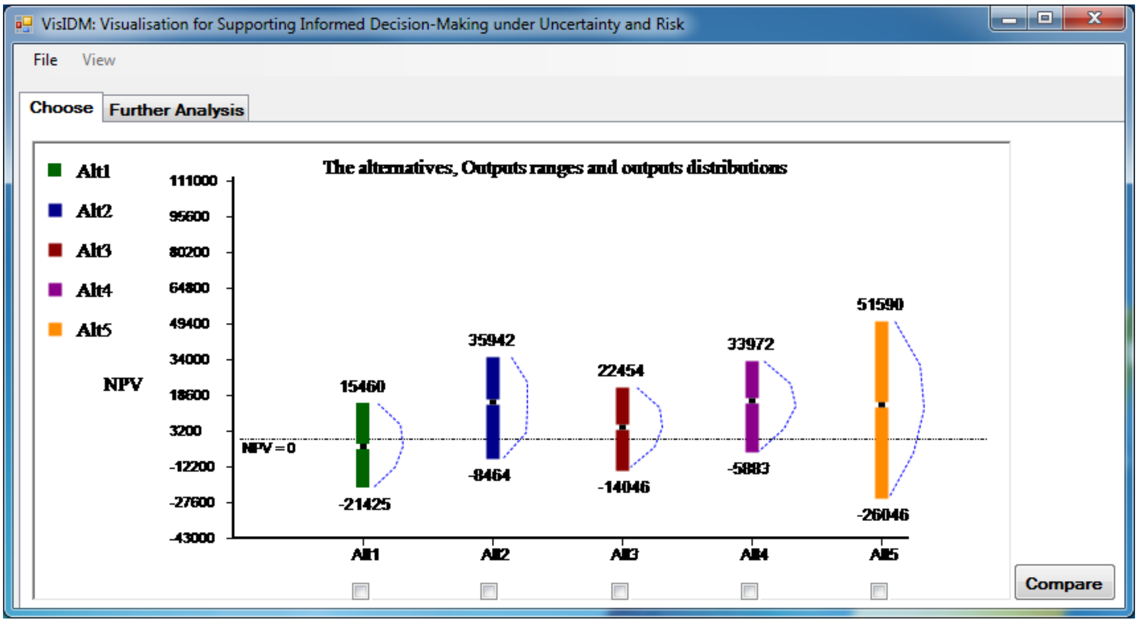


Figure 7.2: A screenshot of the Outcome Bars interface

Table 7.1: Types of information identified and used by the 12 participants to perform the operations and their frequency of use.

Type of information	**Frequency of use**
Minimum and maximum NPV values of each alternative	12
Range of negative and positive NPV values	5
Probability distribution of possible NPV values	2
Mean value of possible NPV values	3

As shown in Table 7.1, all the 12 participants were able to identify the maximum and minimum possible NPV values of each alternative. These two values were interpreted by participants as the maximum potential profit and loss resulting from each alternative, respectively. Accordingly, they used these values to evaluate and compare alternatives in terms of the maximum profit and loss potential. However, the majority of participants (10 out of 12) did not solely base their final decisions on the two extremes of NPV of each alternative. Rather, they preferred to make further comparisons of alternatives based on other information they extracted from the Outcome Bars interface.

Five out of the 12 participants made further comparisons of alternatives based on the proportion of positive and negative NPV values. However, this proportion was incorrectly interpreted by these participants as the probability of making a profit and loss, respectively. For example, one participant who used the proportion of positive and negative NPV values to compare alternatives said: *"alternatives 3 and 5 cannot be best choices because both of them have a huge range of negative NPV values so you have a big chance to make a loss."* This extract indicates that the participant's understanding of the probability of making a loss may be flawed. He/she is interpreting the range of negative NPV values to mean a *"big chance of making a loss"* whereas it really means a *"chance of making a big loss."*

Two of the five participants who used the proportion of positive and negative NPV values made further comparisons between alternatives based on the probability distribution of possible NPV values of each alternative. These participants were attracted by how stable the probability distribution is around the mean value (the black part of Outcome Bars in Figure 7.2). For example, one participant when he/she was pointing to alternative 2 said: *"What I noticed, here is some flat, flat means stable; there is more chance of getting these values around the mean."* Although this could be a correct interpretation in some cases, such as that of alternative 2, the opposite could be true in other cases, specifically when the distribution is flat or stable, but close to the outcomes bar.

Three out of the 12 participants utilised the mean value of the possible NPV values of each alternative to rank and choose the most preferred alternative. According to these participants, the higher the mean value of possible NPV values, the better the decision alternative. For example, one participant commented: *"my criterion is that...if we have a higher mean value I'll definitely choose this alternative."* However, these participants faced a difficulty in using the mean value to distinguish between alternatives 2 and 4 as their mean values were similar (see the black part of Outcome Bars of alternatives 2 and 4 in Figure 7.2). To help in distinguishing between the mean values, one participant suggested presenting a numerical value with the visual cue of the mean value.

Interestingly, none of the participants used the probability distribution of possible NPV values to evaluate the risk (i.e. the probability of making a loss). However, the content analysis of the participants' responses showed that the term 'risk' was used frequently as an important criterion for deciding upon preferred alternatives. For example, the following extract from the evaluation of one participant justifies the selection of alternatives 2 and 4 as the most preferred alternatives: *"I prefer to go with guaranteed* *option of minimizing risk rather than optimize the profit."* Another participant said: *"I gave priority to minimising the risk rather than maximising the profit and I chose based on that."* According to these extracts, it appears that these participants used the term 'risk' to refer to the maximum potential loss. The same issue of risk perception was also observed from the other participants' responses. They discussed the risk in general to refer to the potential loss without even clearly identifying whether their perception of risk was affected by the probability of this loss.

As a result of comparisons between alternatives, the two alternatives 1 and 3 were eliminated by all participants. This is mainly because both of them were not attractive in terms of the profit and loss potential according to their maximum and minimum NPV values (see Figure 7.2). The remaining alternatives 2, 4 and 5 were further compared by participants to determine and rank the two most preferred. Figure 7.3 shows that eight out of 12 participants ranked alternative 4 as the first preferred alternative and alternative 2 as the second preferred. Three participants ranked alternative 2 as the first preferred alternative and alternative 4 as the second preferred. This is mainly because both alternatives 2 and 4 involve lower potential losses compared to other alternatives ($-8464 and $-5883, respectively, see Figure 7.2), and at the same time acceptable potential profits ($35942 and $33972, respectively). Although alternative 5 has higher profit potential compared to alternatives 2 and 4, it was eliminated by most participants because the maximum loss potential of alternative 5 (-$26046) is also higher than that of alternative 2 (-$8464) and 4 (-$5883) as shown in Figure 7.2. Consequently, only one of the 12 participants selected alternatives 2 and 5 as the two most preferred alternatives. This participant ranked alternatives 5 and 2 as the first and second preferred alternatives, respectively.

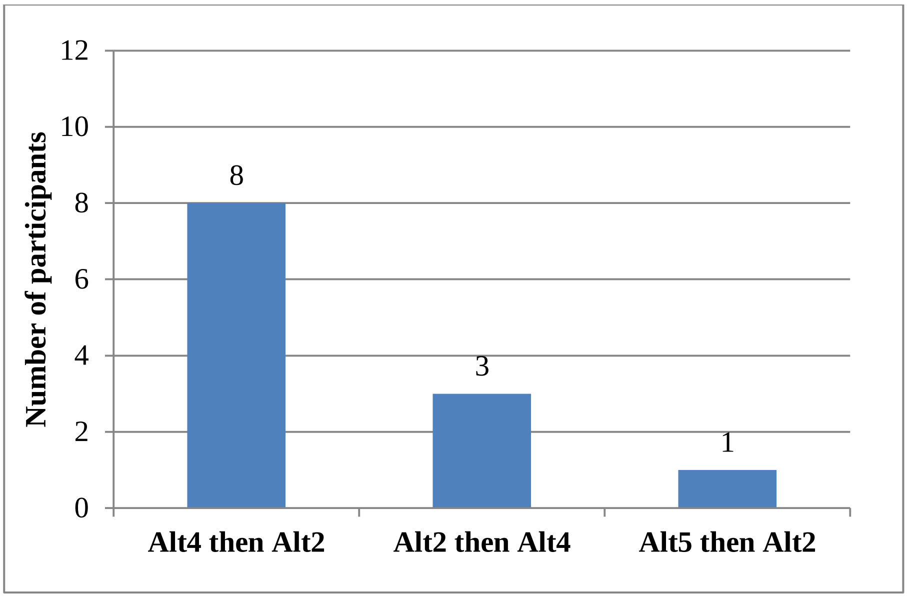


Figure 7.3: Frequency of ranking the two most preferred alternatives using the Outcome Bars interface

To choose the most preferred alternative, the participants made further comparisons between the two most preferred alternatives using the information shown in Table 7.1. Figure 7.4 shows that most participants (8 out of 12) considered alternative 4 as the most preferred alternative. These participants justified their choice mainly on the basis of the low risk of making a loss associated with alternative 4. However, the analysis of the results shows that these participants misused the term ‘Risk’. They perceived alternative 4 as the least risky alternative according to the potential loss it entails, rather than the probability of this loss. In addition to the perceived risk of making a loss, these participants found that the maximum potential profit (i.e. maximum NPV) of alternative 4 is acceptable and the proportion of positive NPV values is relatively high.

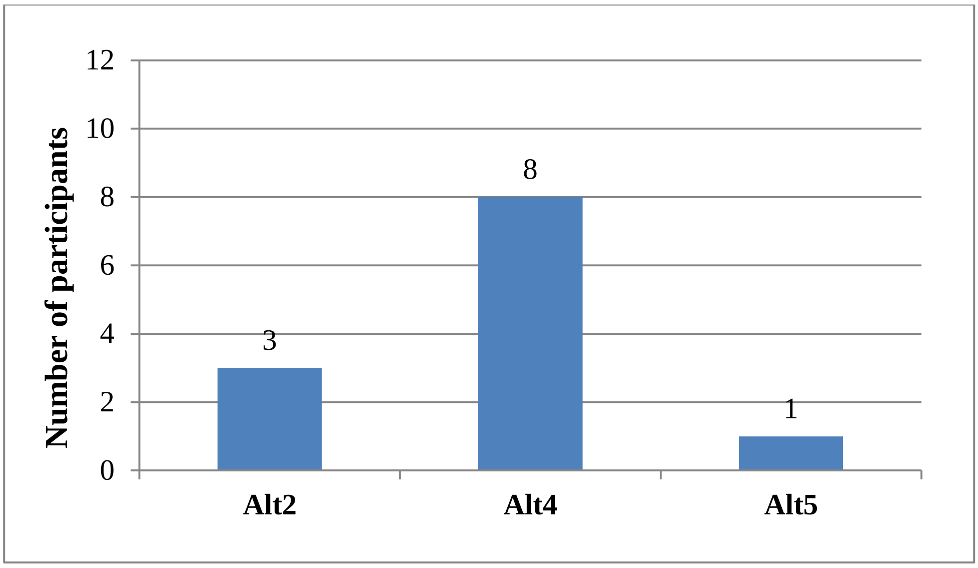


Figure 7.4: Number of times each alternative was considered the most preferred alternative using the Outcome Bars interface

Three out of 12 participants considered alternative 2 as the most preferred alternative. In addition to the maximum potential loss, these participants based their choice on the maximum potential profit each alternative entails. These participants considered alternatives 2 and 4 as the two most preferred alternatives according to their maximum potential loss (i.e. minimum NPV). To choose the best among them, they further compared the two alternatives 2 and 4 in terms of the maximum potential profit. They recognised that alternative 2 would result in a higher potential profit according to its maximum NPV ($35942) compared to alternative 4 ($33972). Two of these three participants also extended their comparisons between alternatives 2 and 4 to include the mean value of NPV values. They noticed that the mean value of NPV values of alternative 2 is slightly higher than that of alternative 4 (see Figure 7.2).

Only one of the 12 participants considered alternative 5 as the most preferred alternative. This participant showed a higher preference for maximising the potential profit instead of minimising the potential loss. This participant found that alternative 5 has the highest potential profit according to its maximum NPV ($51590, see Figure 7.2). To justify his or her choice, the participant said: *"Although the risk is high the profit is still high so I'll go with alternative 5."* Again, according to this extract, the participant perceived the risk of making a loss to mean the maximum potential loss rather than the probability of obtaining this loss.

7.2.1 Main findings

The content analysis of the results led to the following findings related to the implications of the Outcome Bars interface on informed decision-making under uncertainty and risk:

- **Range of possible outcomes**: all participants used the range of possible outcomes and their extreme values to evaluate and compare alternatives in terms of the worst and best possible outcomes.

- **Probability distribution of outcomes**: only a few participants used the probability distribution of possible outcomes to evaluate and compare alternatives.

- **Mean value of outcomes**: only a few participants used the mean value of the possible outcomes of each alternative to rank and choose the most preferred alternative.

- **Proportion of positive and negative outcomes**: fewer than half of participants used the proportion of positive and negative NPV values. However, this proportion was incorrectly interpreted by these participants as the probability of making a profit and loss, respectively.

- **Risk perception**: The majority of participants considered the risk to refer to the potential loss without clearly identifying whether their perception of risk was affected by the probability of this loss.

7.3 Sequence of operations pursued by participants using the Risk and Likelihood Bars interface

Figure 7.5 shows the sequence of operations pursued by participants to arrive at the final ranking of the two preferred alternatives and choose the better among them while using the Risk and Likelihood Bars interface shown in Figure 7.6. Table 7.2 lists the types of information extracted and used by participants to perform these operations and their frequency of use.

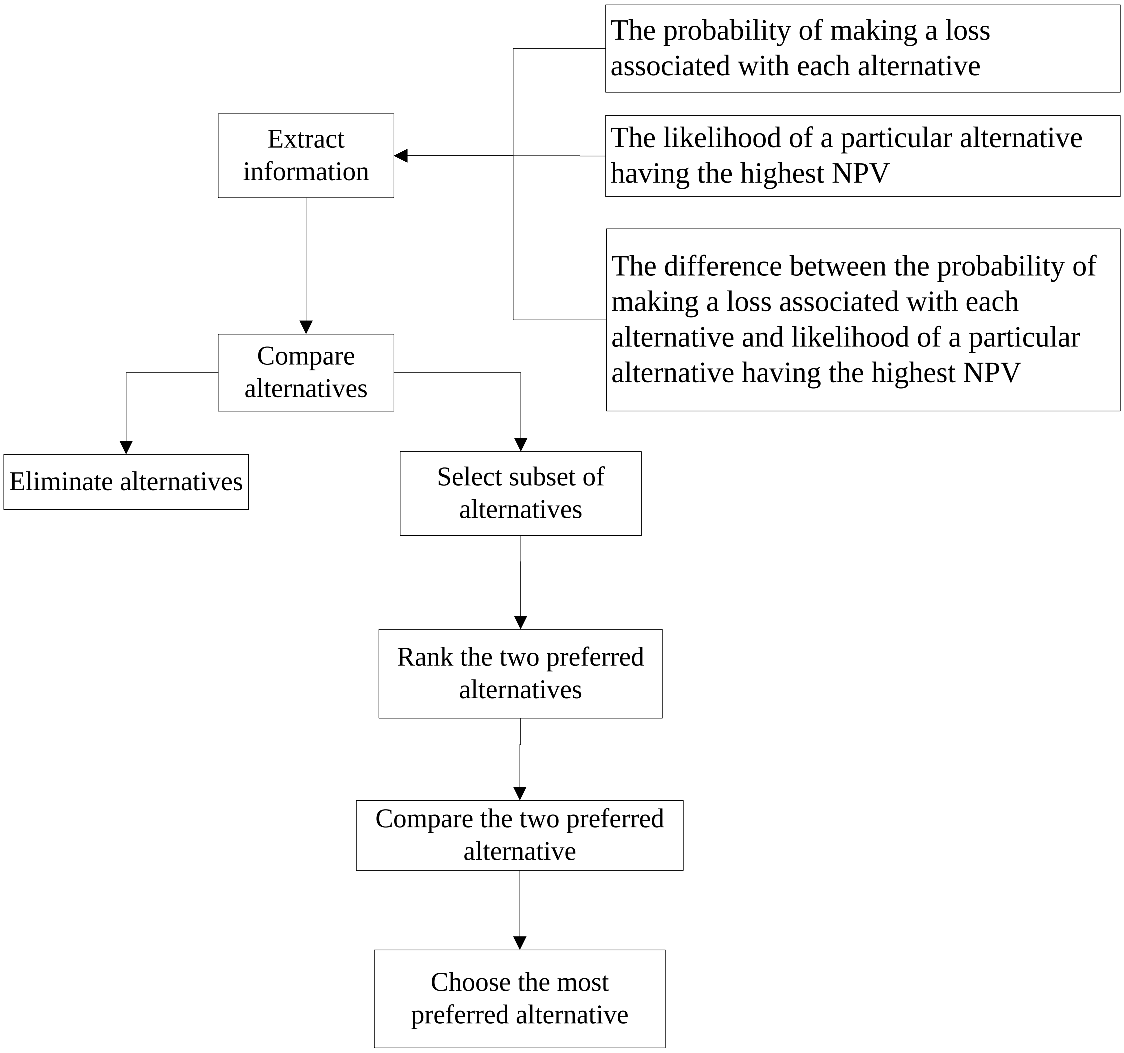


Figure 7.5: The sequence of operations performed by participants using the 'Risk and Likelihood Bars' interface.

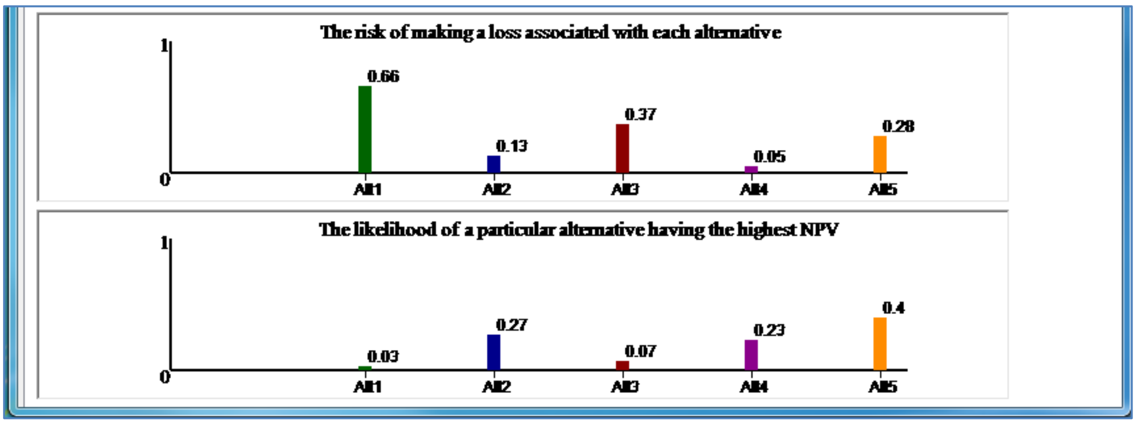


Figure 7.6: A screenshot of the Risk and Likelihood Bars interface

Table 7.2: Types of information used by participants to perform the operations and their frequency of use.

Type of information	Frequency of use
The probability of making a loss associated with each alternative	12
The likelihood of a particular alternative having the highest NPV	5
The difference between the probability of making a loss associated with each alternative and likelihood of a particular alternative having the highest NPV	3

As discussed in Section 5.5.1, the Risk and Likelihood Bars interface displays information on the overall probability of undesirable outcomes (in this case the probability of making a loss) associated with each alternative. It also displays information about the likelihood of a particular alternative having the highest NPV; i.e. the percentage of NPV values of a particular alternative that are higher than all NPV values of other alternatives. In addition to these types of information, it was observed that some participants derived additional information by calculating the difference between the probability of making a loss associated with an alternative and the likelihood of this alternative having the highest NPV. This calculation was made because these participants misinterpreted the likelihood of an alternative having the highest NPV as the probability of making a profit. Thus, they thought that calculating the difference between the probability of making a loss and likelihood that this alternative having the highest NPV would provide them with additional useful information as will be discussed later.

As illustrated in Table 7.2, all the 12 participants utilised the information about the probability of making a loss to compare alternatives. Also, they used this information to confirm the previous decisions they had made when using the Outcome Bars interface. Fewer than half of participants (5 out of 12) performed further comparisons between alternatives based on the likelihood of a particular alternative having the highest NPV. However, it was observed that this information was incorrectly interpreted by these participants as the probability of making a profit (in this case the probability of positive

NPV values). For example, one participant commented: *“I’ve gotten now information about the probability of making a loss and likelihood of making profit so it makes me more informed.”* This misinterpretation affected the assessment of alternatives in terms of the potential profit. For example, as a result of comparing the two alternatives 2 and 4, one participant considered alternative 2 as the first preferred alternative because it has higher probability of making a profit (27%) compared to alternative 4 (23%), as shown in the bottom panel of Figure 7.6.

Conversely, over half of participants (7 out of 12) did not utilise the information about the likelihood of a particular alternative having the highest NPV. Hence, this information did not affect their final ranking of the two most preferred alternatives and selection of the most preferred one. These participants found the likelihood of a particular alternative having the highest NPV difficult to understand and misleading. For example, one participant commented: *“this visualization adds more information but it can be misleading because of the bars related to the likelihood because it’s difficult to utilize information of the likelihood bars.”* Other participant commented: *“Initially I thought that the likelihood bars would be helpful, but they didn’t add much to the previous information. Also, I found them confusing.”*

Three out of 12 participants made further comparisons between alternatives based on information derived by calculating a difference score for each alternative. The difference score was obtained by subtracting the likelihood of a particular alternative having the highest NPV, which was (incorrectly) interpreted as the probability of making a profit, from the probability of making a loss. For example, while comparing alternatives 2 and 4, one participant preferred alternative 4 because the difference score of alternative 4 (23% - 5% = 18%) is higher than that of alternative 2 (27% - 13% = 14%), as shown in Figure 7.6.

As a result of comparisons between alternatives, the two alternatives 1 and 3 were considered as the least desirable alternatives by all participants. Hence they were eliminated as they involve high probability of making a loss (66% and 37%, respectively), as shown in the top panel of Figure 7.6. The remaining alternatives 2, 4 and 5 were further compared in terms of the probability of making a loss and profit potential. Figure 7.7 shows that most participants (9 out of 12) ranked alternative 4 as the first preferred alternative, followed by alternative 2 as the second preferred. This was mainly because the probability of making a loss associated with alternative 4 (5%) is less than that associated with alternative 2 (13%). In contrast, two out of 12 participants ranked alternative 2 as the first preferred alternative followed by alternative 4 as the second preferred. These participants (incorrectly) interpreted the likelihood of a particular alternative having the highest NPV as the probability of making a profit. Consequently, they ranked alternative 2 as the first preferred alternative because it has higher likelihood of having highest NPV (27%) compared to alternative 4 (23%). Only one of the 12 participants ranked alternatives 5 and 2 as the first and second most preferred, respectively.

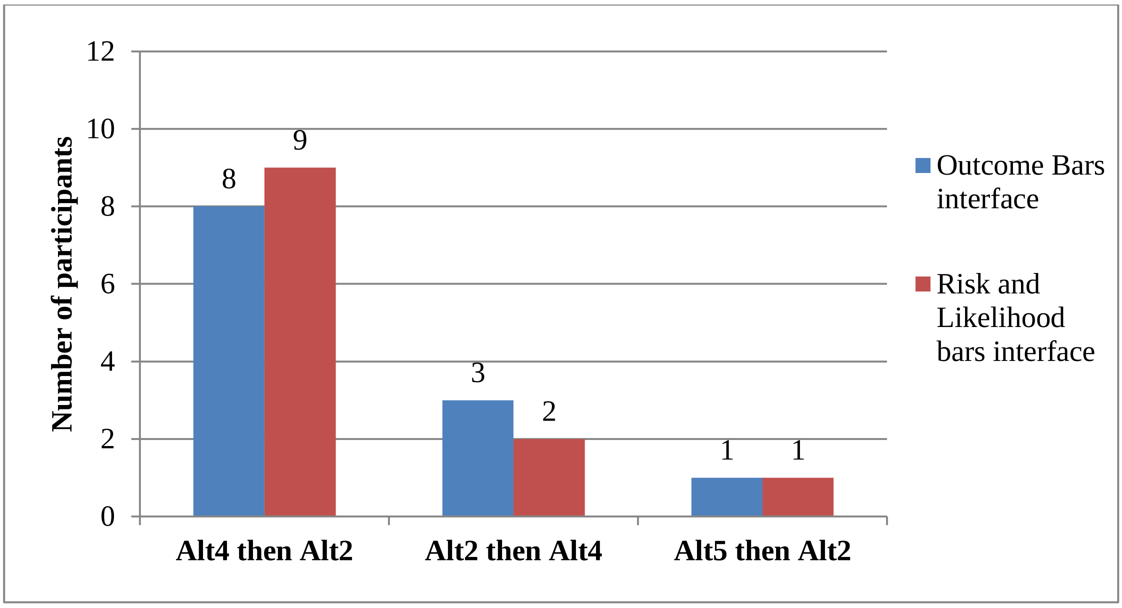


Figure 7.7: Frequency of ranking the two most preferred alternatives using the interfaces of Outcome Bars and Risk and Likelihood Bars

As shown in Figure 7.7, while using the Risk and Likelihood Bars interface, one participant among those who ranked alternatives 2 and 4 as the first and second while using the Outcome Bars interface switched the order of the two alternatives. According to this participant, the Risk and Likelihood Bars interface provided him/her with more direct information about the probability of making a loss compared to the Outcome Bars interface. Accordingly, he/she recognised that the overall risk of making a loss associated with alternative 4 (5%) is less than that associated with alternative 2 (13%).

Consequently, he/she changed his or her mind about the order of alternatives 2 and 4 as he/she gave a priority to minimise the potential loss rather than maximise the profit.

To choose the best alternative, the participants made further comparisons between the two most preferred alternatives. Figure 7.8 shows that the majority of participants (10 out of 12) agreed on considering alternative 4 the most preferred alternative. This was mainly because alternative 4 is the least risky alternative as shown in the middle panel of Figure 7.6. For example, one participant justified his/ her choice by saying: *"I'm not a risk taker so I prefer to minimize the risk as much as possible. Alternative 4 has the lowest risk. I'm not motivated by the profit, but I'm motivated by the risk."* One participant considered alternative 2 as the most preferred alternative. To justify his choice, the participant said: *"alternative 4 has lower risk but alternative 2 promise me higher profit."* One other participant considered alternative 5 as the most preferred alternative. To justify his choice, the participant said: *"In business if a project has a high risk you have a high likelihood of having high profit, basically this why I chose Alternative 5."*

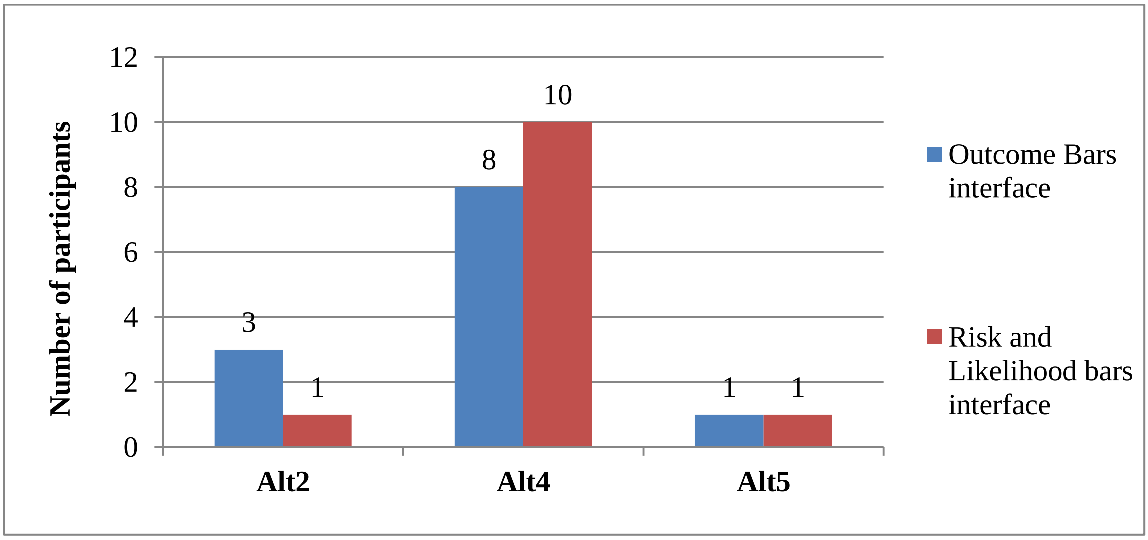


Figure 7.8: Number of time each alternative was considered the most preferred alternative using the 'Outcome Bars' and 'Risk and Likelihood Bars' interfaces

As shown in Figure 7.8, the number of participants who considered alternative 4 as the most preferred alternative increased from 8 to 10 using the Risk and Likelihood Bars interface. In contrast, the number of participants who considered alternative 2 as the most preferred alternative decreased from 3 to 1. This difference can be interpreted by noticing that 2 of the participants who considered alternative 2 as the most preferred alternative switched from alternative 2 to alternative 4 as the most preferred alternative. According to these participants, the Risk and Likelihood Bars interface helped them to be more informed about the probability of making a loss associated with each alternative. One participant commented: *"Here I have better information than the previous one. I feel more informed because here I've gotten more information about the likelihood of getting loss so it is better than just having information about how much money you will make as a profit or loss."*

7.3.1 Main findings

The content analysis of the results led to the following findings related to the implications of the Risk and Likelihood Bars interface on informed decision-making under uncertainty and risk:

- **The overall risk**: all participants used the Risk Bars that show information about the overall probability of making a loss associated with each alternative to compare alternatives and confirm their previous decisions they had made when using the Outcome Bars interface.

- **The likelihood of a particular alternative having the highest outcome**: all participants misinterpreted and misused the Likelihood Bars that show the percentage at which an alternative would have the highest outcomes. They found this information to be misleading and not helpful in facilitating informed decisions.

- **Additional information**: some participants derived additional information by calculating the difference between the probability of making a loss associated with an alternative and the likelihood that this alternative having the highest NPV, which was misinterpreted as the probability of making a profit.

7.4 Sequence of operations pursued by participants using the Risk Explorer interface

Figure 7.9 shows the sequence of operations pursued by participants to arrive at the final ranking of the two most preferred alternatives and choose the best among them while using the Risk Explorer interface shown in Figure 7.10.

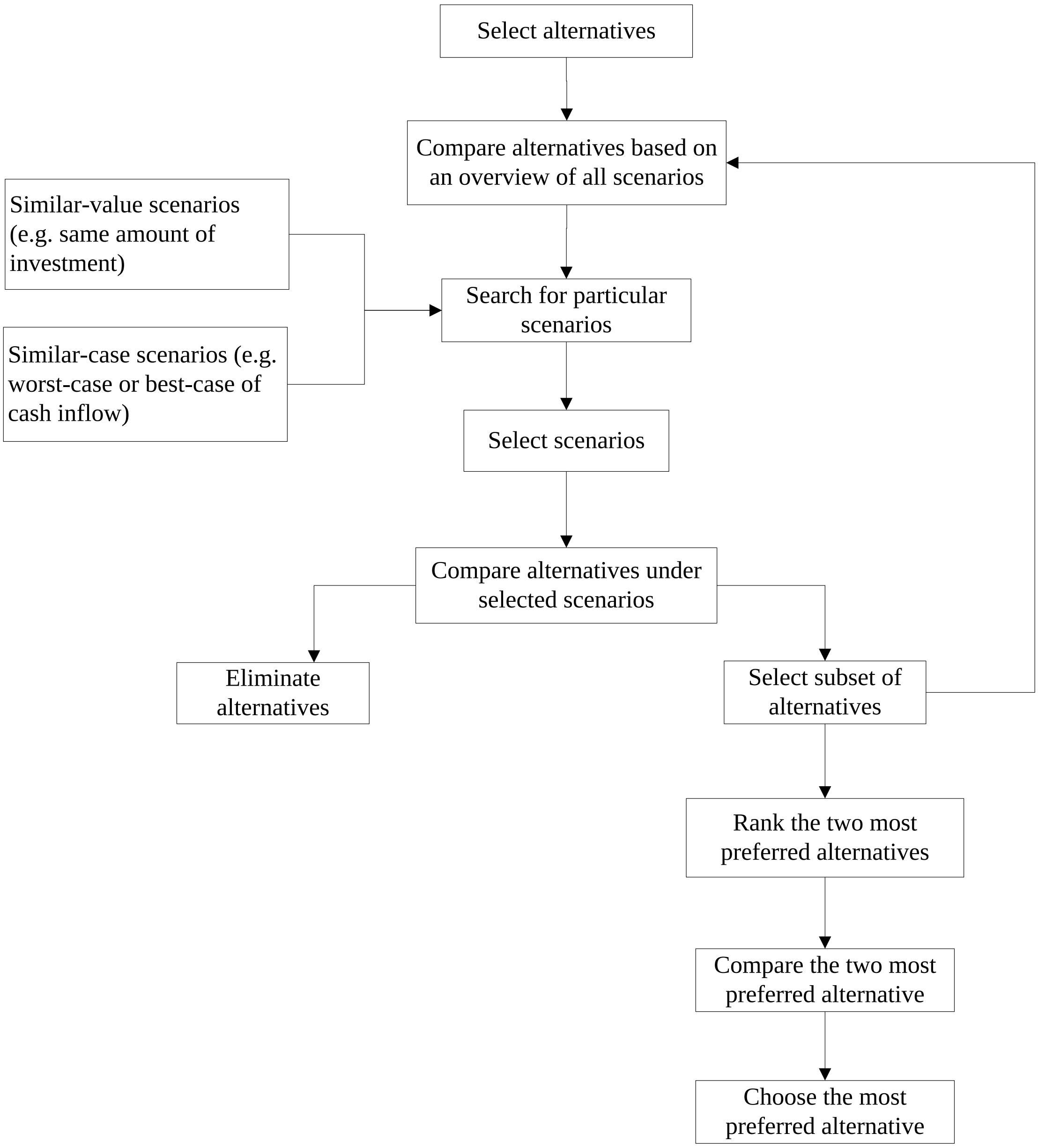


Figure 7.9: The operations performed by participants during the use of the Risk Explorer interface

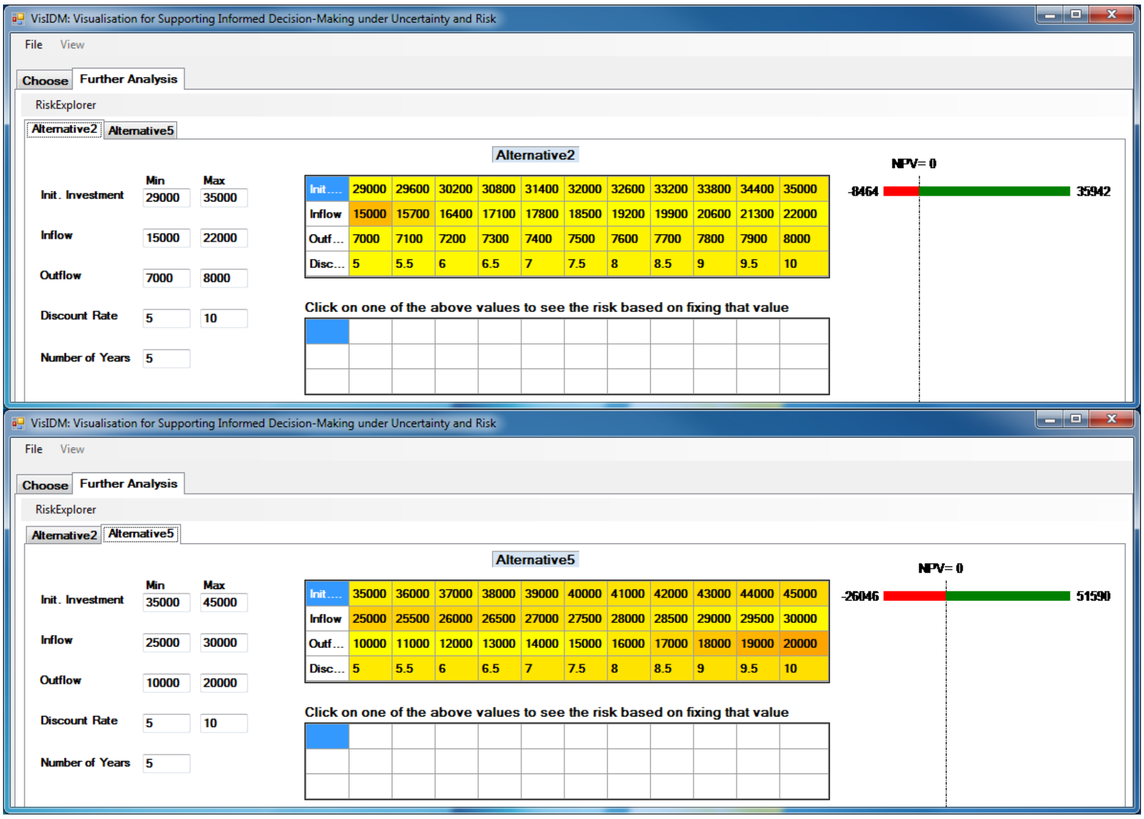


Figure 7.10: A screenshot of the Risk Explorer interface after selecting alternatives 2 and 5 for analysis and exploration

As discussed in Section 5.5.2, the Risk Explorer interface allows the exploration of alternatives either consecutively or simultaneously. However, it was observed that the participants preferred to explore and compare alternatives simultaneously rather than consecutively. It was also observed that most participants preferred to start by analysing and exploring the alternatives that were chosen as most preferred alternatives during the use of the previous interfaces. For example, one participant commented: *"It should be based on my previous chosen alternatives. Because I chose alternatives 2 and 4 so I will compare 2 and 4 first."* Since all participants considered alternatives 2, 4 or 5 as their most preferred alternatives at the previous interfaces, the operations were mostly performed for these alternatives.

To arrive at a final ranking of the two preferred alternatives and choose the best among them, the participants conducted a series of comparisons between alternatives under different scenarios (i.e. different values of input variables). As shown in the top grid of Figure 7.10, there are many possible values corresponding to each input variable, each of which was considered by participants as a possible scenario. The analysis of the results showed that the participants followed three ways for comparing between alternatives: 1) comparison based on an overview of all scenarios; 2) comparison based on similar-value scenarios (e.g. similar or closely similar values of initial investment); and 3) comparison based on similar-case scenarios (e.g. worst-case or best-case scenarios of cash inflow).

Prior to focusing on specific scenarios, all participants made comparisons between alternatives in terms of the probability of making a loss and profit potential based on an overview of all scenarios. To compare between alternatives in terms of the probability of making a loss, the participants looked first at the colour variation across the grid cells of each alternative under investigation. For example, when comparing alternatives 2 and 5, many participants perceived that the probability of making a loss with alternative 5 is higher than that associated with alternative 2 according to the colour variation across the cells; the colour is darker in the grid of alternative 5 (see Figure 7.10). One participant said: *"alternative 2 is better than alternative 5 because when I have a look on every single scenario in alternative 2, I see that all is safer compared to alternative 5 because in alternative 5 there are several options that have high risk, but alternative 2 for most options the risk is low and acceptable for me."* Another participant commented: *"For alternative 5, the risk is high in many cases I can notice that from the colour."*

To compare alternatives in terms of their profit and loss potential, the participants used the red/green bar shown to the right of the corresponding gird (see Figure 7.10). For example, when comparing between alternatives 2 and 5, many participants perceived that the maximum profit associated with alternative 5 is higher than that associated with alternative 2, but at the same time, the maximum loss is also higher for alternative 5. However, only a few participants (2 out of 12) found it sufficient to compare and then rank alternatives based on an overview of the probability of making a loss and profit associated with each alternative. The majority of participants (10 out of 12) preferred to perform further comparisons between alternatives under smaller, more focused set of scenarios.

Some participants made comparisons between alternatives in terms of the probability of making a loss and profit potential under similar-value scenarios (e.g., similar amount of initial investment). To do so, they fixed similar or closely similar values of one or more variables. For example, as shown in Figure 7.11, one participant made a comparison between alternative 2 and 5 based on fixing the two variables initial investment at $35000 and discount rate at 10%. He/she fixed the initial investment at $35000 in the top grid of each alternative. Then, he/she fixed the discount rate at 10% in the resulting grid of each alternative. Other participants chose different variables (e.g. one participant made a comparison between alternative 2 and 4 based on fixing similar or closely similar values of cash inflow and initial investment).

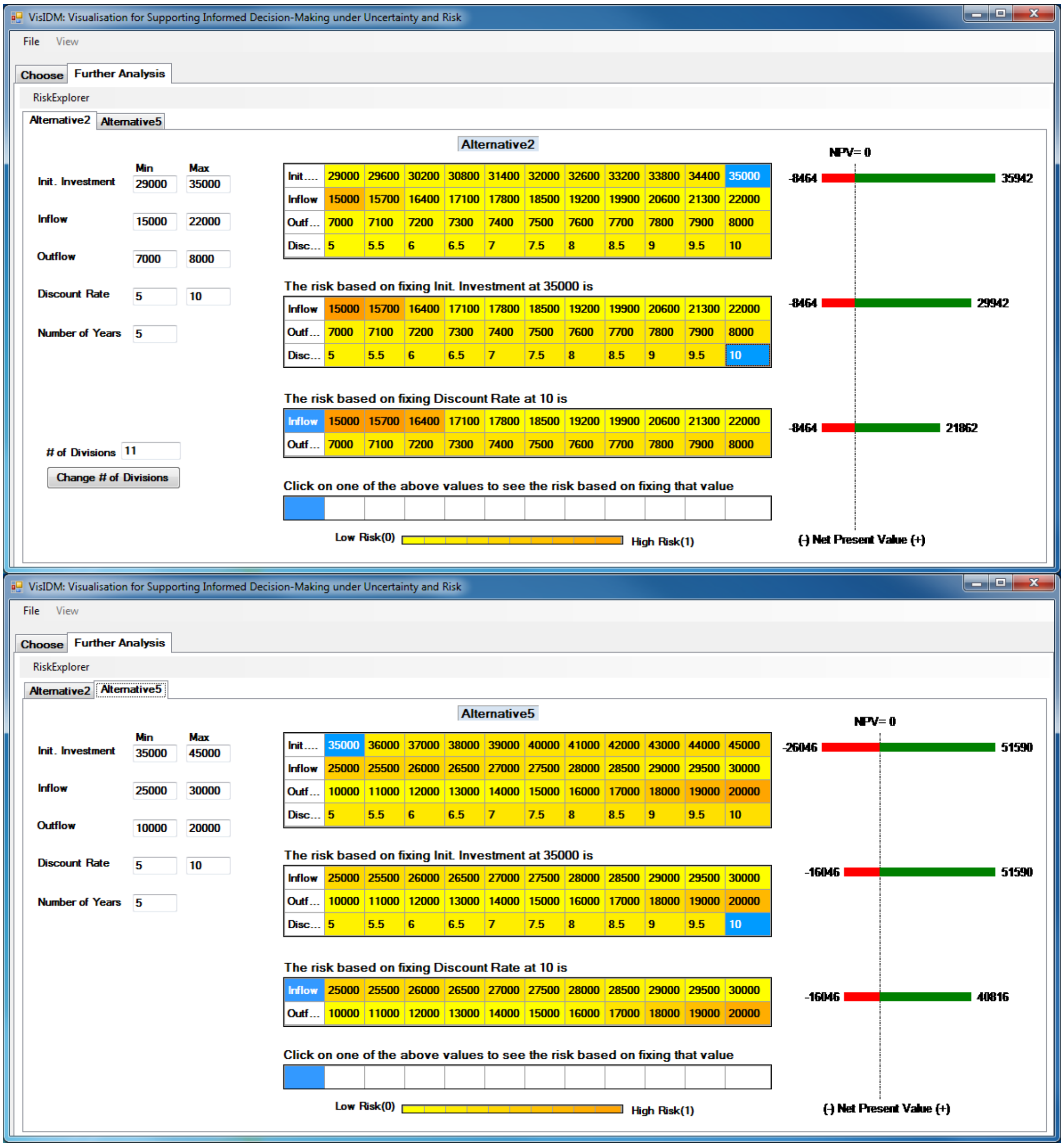


Figure 7.11: A new grid and red/green bar for alternatives 2 and 5 after holding the initial investment at $35000 and discount rate at 10%

Some participants made comparisons between alternatives in terms of the probability of making a loss and profit potential under similar-case scenarios (e.g., worst-case or best-case scenarios). For example, one participant made a comparison between alternative 2 and 4 under pessimistic (worst) and optimistic (best) estimates of cash inflow. For this purpose, he/she identified and fixed the worst (minimum) and best (maximum) estimates of cash inflow of both alternatives. Then, he/she explored the resulting probability of making a loss and range of outcomes (i.e. range of possible NPV values) of each alternative. Other participants used different variables (e.g. participant 7 made a comparison between alternatives 2 and 5 under worst and best initial investment). Some participants also made comparisons between alternatives under worst and best cases of more than one variable. For example, one participant made a comparison between alternative 2 and 4 in terms of the probability of making a loss and profit potential based on fixing the cash inflow at the minimum value and discount rate at the maximum value.

During the comparisons of alternatives, the participants adopted two ways to identify and evaluate the risk of making a loss associated with each alternative. On the one hand, some participants relied on the colour variation across the cells of resulting grids. This way was adopted by participants when the difference between the probability of making a loss of one alternative and the probability of making a loss of another was clear and can be distinguished. For example, as shown in Figure 7.12, one participant performed a comparison between alternative 1 and 2 under a discount rate of 10%. He/she observed that the colour of many cells in the grids of alternative 1 is much darker than that of alternative 2. Consequently, he/she perceived that the risk of making a loss associated with alternative 1 is much higher than that associated with alternative 2 with the discount rate of 10%.

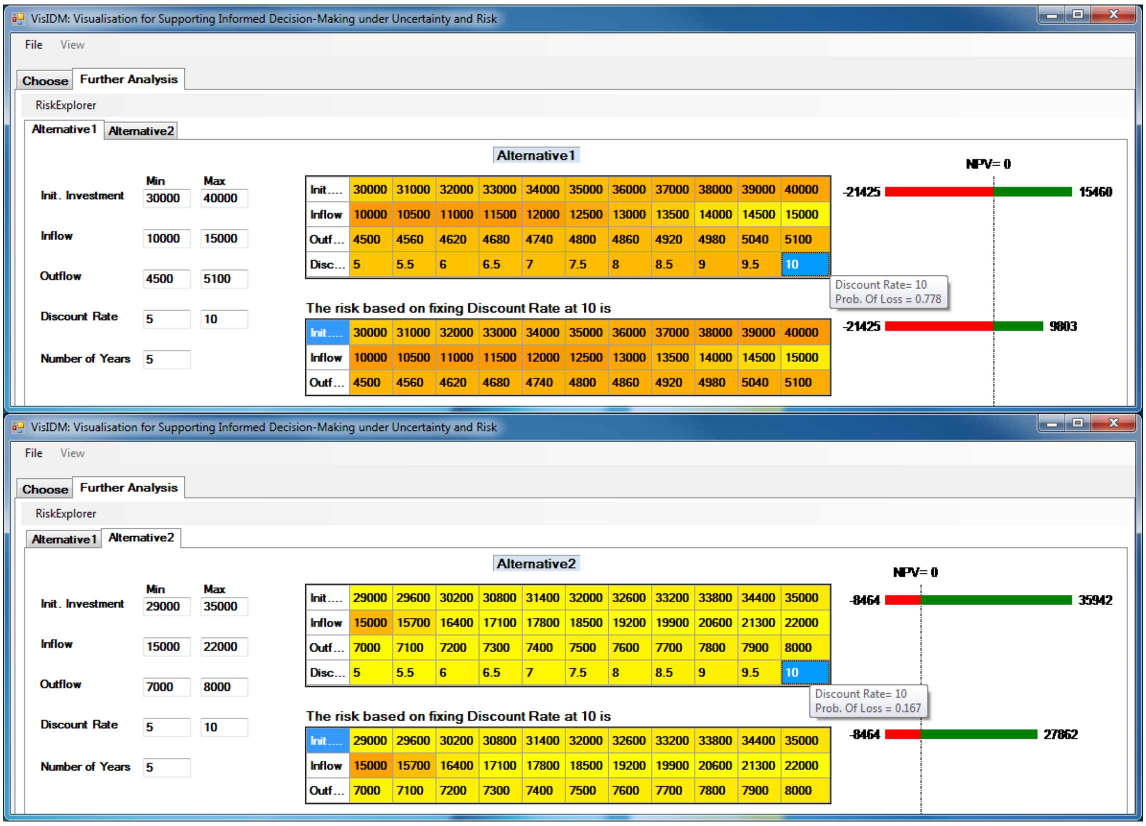


Figure 7.12: A screenshot of the Risk Explorer interface after selecting alternatives 1 and 2 for analysis and exploration and holding the discount rate at 10%

On the other hand, in many scenarios, the participants were not able to compare alternatives in terms of the risk of making a loss by observing the colour variation across the cells; particularly, when the scenarios had similar risk profiles. For example, as shown in Figure 7.13, under initial investment of $35000, both alternatives 2 and 5 had nearly similar overall risk profiles (i.e. nearly similar probability of making a loss). Hence, it was hard for participants to identify which alternative involved higher risk of making a loss by observing the colour variation across the cells of the resulting grids. In such cases, the participants relied on the red/green bars to identify the risk of making a loss. In particular, the participants used the maximum potential loss (i.e. minimum NPV), and the proportion of negative NPV values (the red part of the resulting bars) to form their impressions about the risk, regardless of probability.

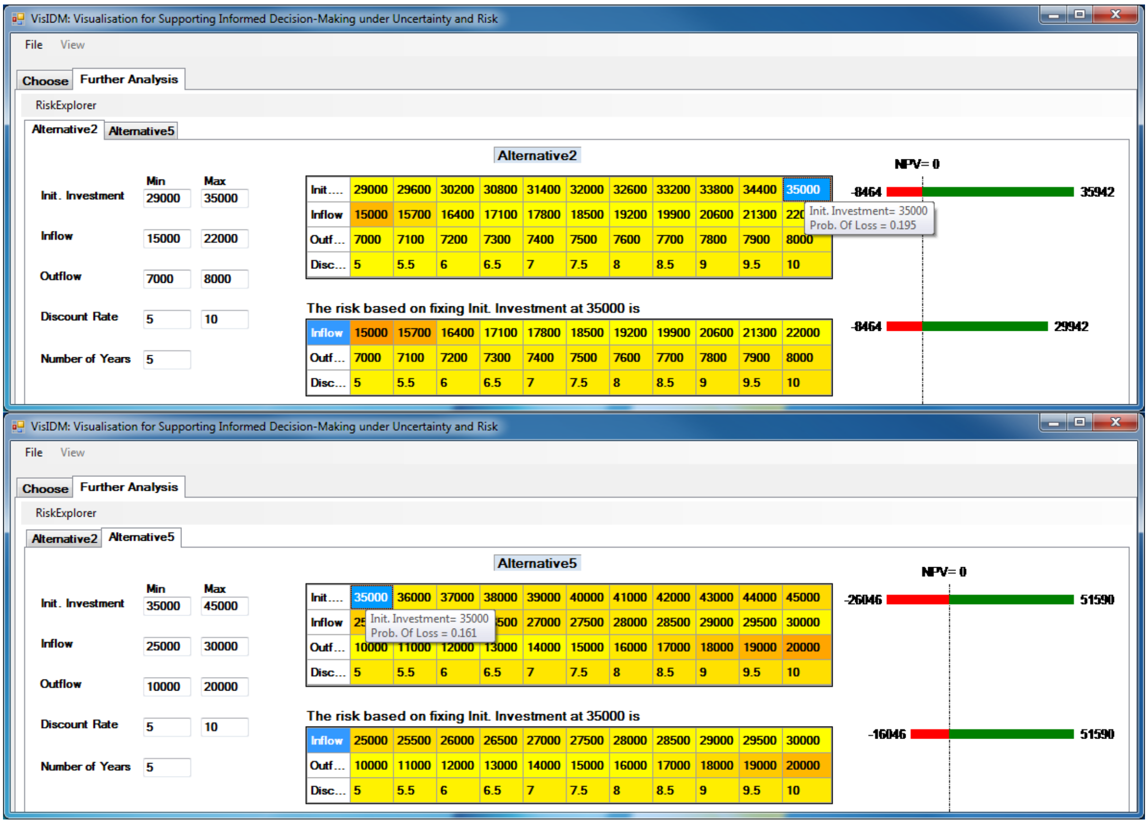


Figure 7.13: A screenshot of the Risk Explorer interface after selecting alternatives 2 and 5 for analysis and exploration and holding the initial investment at $35000

Contrary to expectations, in the cases as those described above, the participants discussed the risk in general to refer to the maximum potential loss without even clearly identifying whether their perception was affected by the probability of occurrence of this loss. For example, many participants perceived alternative 5 as more risky than alternative 2 under initial investment of $35000, without even trying to know the numerical value of the risk (i.e. the probability information). To retrieve a numerical value of the risk, the participants only needed to hover over the corresponding cell to view a message box (a pop-up window) contains the numerical value of the risk (i.e. the probability information). For example, as shown in Figure 7.13, if the participants retrieved numerical values of the risk under initial investment of $35000, they will find that the probability of making a loss of alternative 5 (16.1%) is lower than that of alternative 2 (19.5%). However, the participants revealed little/no interest in obtaining numerical information about the risk probability, although they clearly understood how to do so in the practice phase of this study.

Based on the comparisons made between alternatives, the participants chose the two most preferred alternatives and then ranked them. The results revealed that all participants showed greater preference for minimising the loss rather than optimising the profit. Hence, using the Risk Explorer interface, all participants selected alternatives 2 and 4 as the most preferred alternatives. As shown in Figure 7.14, the majority (11 out of 12) ranked alternative 4 as the first preferred alternative then alternative 2 as the second. Only one participant showed a higher preference for alternative 2 over alternative 4. Although alternative 5 had a higher profit potential (i.e. higher NPV) compared to alternatives 2 and 4, it was eliminated by all participants because they perceived that it involved a higher probability of making a loss under the scenarios they investigated.

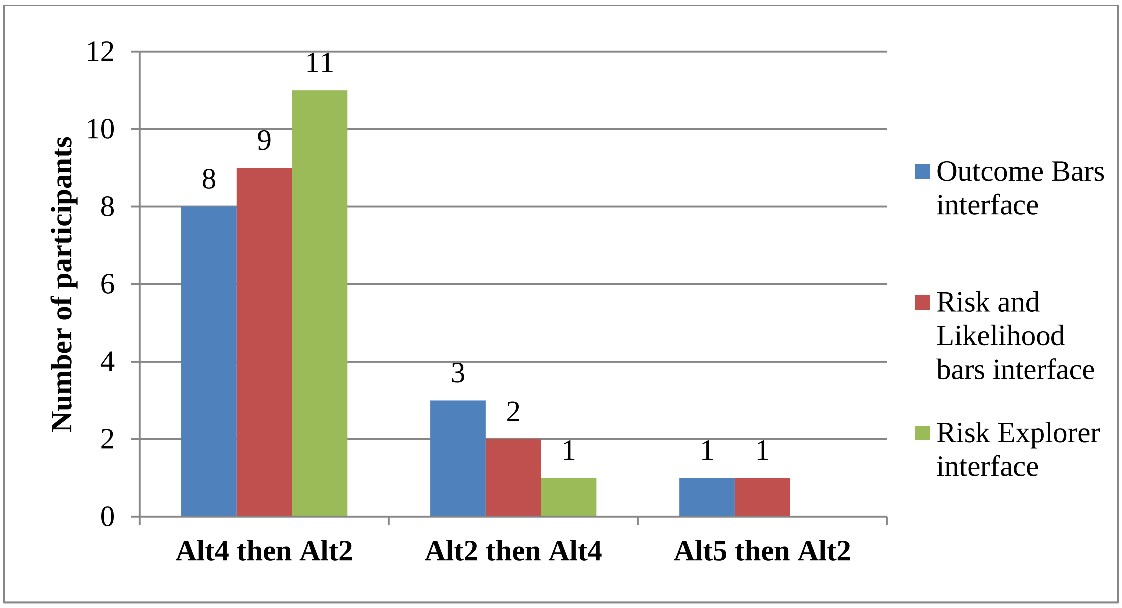


Figure 7.14: The frequency of ranking the two most preferred alternatives

To choose the most preferred alternative, the participants made further comparisons between the two most preferred alternatives under different scenarios. As shown in Figure 7.15, the majority of participants (11 out of 12) agreed on selecting alternative 4 as the most preferred alternative. Only one of the 12 participants selected alternative 2 as the most preferred alternative. The other alternatives 1, 3 and 5 were eliminated by all participants because they involved higher probability of making a loss compared to alternatives 2 and 4. One participant commented: *"I'm adventurer and risk taker but not in money I don't like to regret. Alternative 1,3, and 5 are too risky I mean the fluctuations in the variables- discount rate, inflow and outflow is too risky and you may loss too much under many scenarios."*

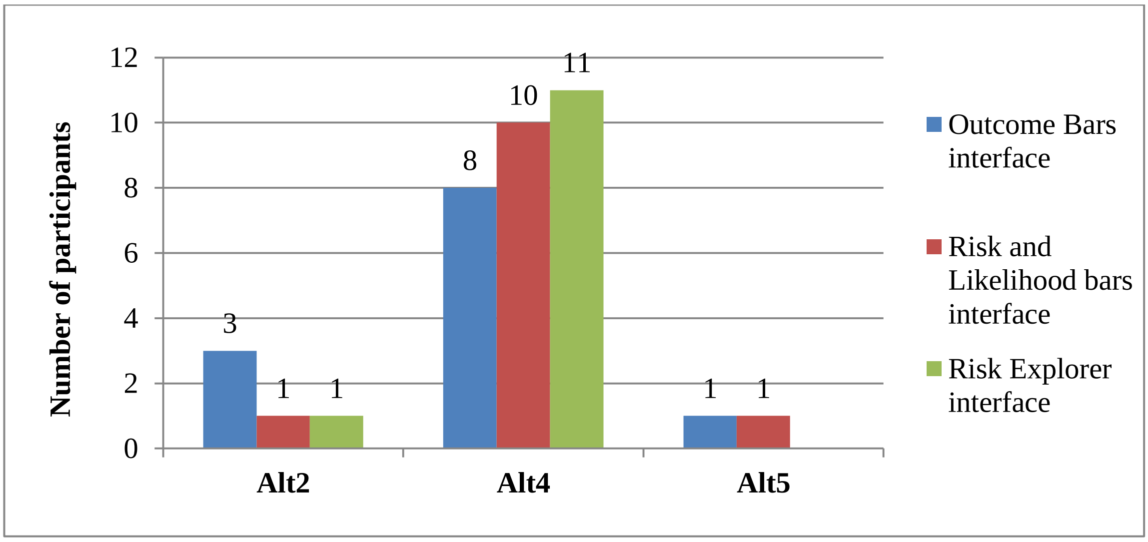


Figure 7.15: The number of times each alternative was considered the most preferred alternative using each of the three interfaces

7.4.1 Main findings

The content analysis of the results led to the following findings related to the implications of the Risk Explorer interface on informed decision-making under uncertainty and risk:

- **Overview of the risk of undesirable outcomes**: all participants used the colour variation across the cells to get an overview of the probability of undesirable outcomes associated with each alternative.
- **Comparing alternatives in terms of the risk of undesirable outcomes**: most participants used the gradations of colours in the grids to compare alternatives when they had different risk profiles.
- **Range of outcomes and their extreme values**: all participants used the red/green bars that show the range of possible outcomes to identify and compare

alternatives in terms of the worst and best possible outcomes. Also, they used the red/green bars to form their impression about the risk of making a loss when the alternatives had similar risk profiles.

- **Exploring the relationships between input variables and risk**: most participants used the colour gradations/variations to explore trends and relationships between the uncertainty in the input variables and probability of undesirable outcomes.
- **The focus and context feature**: most participants used the “focus and context” feature to explore and conduct a series of comparisons between alternatives under different scenarios and levels of detail.
- **The details on demand using pop-up windows**: most participants revealed little/no interest in using the pop-up windows to obtain numerical values of the risk (i.e. probability); although they clearly understood how to do so in the practice phase.
- **Risk perception**: most participants interpreted and used risk information subjectively, and they generally revealed little interest in obtaining information about numerical values of risk (i.e. probability of undesirable outcomes).

7.5 Confidence that the participants had made informed decisions

After completing the questions on ranking the two most preferred alternatives and then choosing the better among them, the participants were asked to rate their level of confidence that they had made informed decisions while using the three interfaces of VisIDM. A five point scale was used to measure each participant’s level of confidence, where 1 = “not confident at all”, and 5 = “very confident.”

Figure 7.16 shows the average level of participants’ confidence that they had made informed decisions while using each of the three interfaces of VisIDM. Using the Outcome Bars interface, the average level of participants’ confidence that they had made informed decisions was relatively high (4.08 out of 5, 81.6%). This level rose slightly to (4.13 out of 5, 82.6%) when using the Risk and Likelihood Bars interface, and then rose to (4.42 out of 5, 88.4%) when using the Risk Explorer interface. These results suggest that the participants believed that they were able to understand and exploit the information provided in each of the three interfaces. They also suggest that as the participants moved from one interface to another, they felt more informed because of the new information they received and their ability to use it in decision-making. For example, one participant expressed about his or her level of confidence that he had made an informed decision when using the Risk Explorer interface by saying: *“Here I can see the relationship between things. I mean the relationships between risk and the factors. It gives me more understanding about the risk and the reasons of having the previous risk. So now I’m feeling more confident because I have all information I need.”*

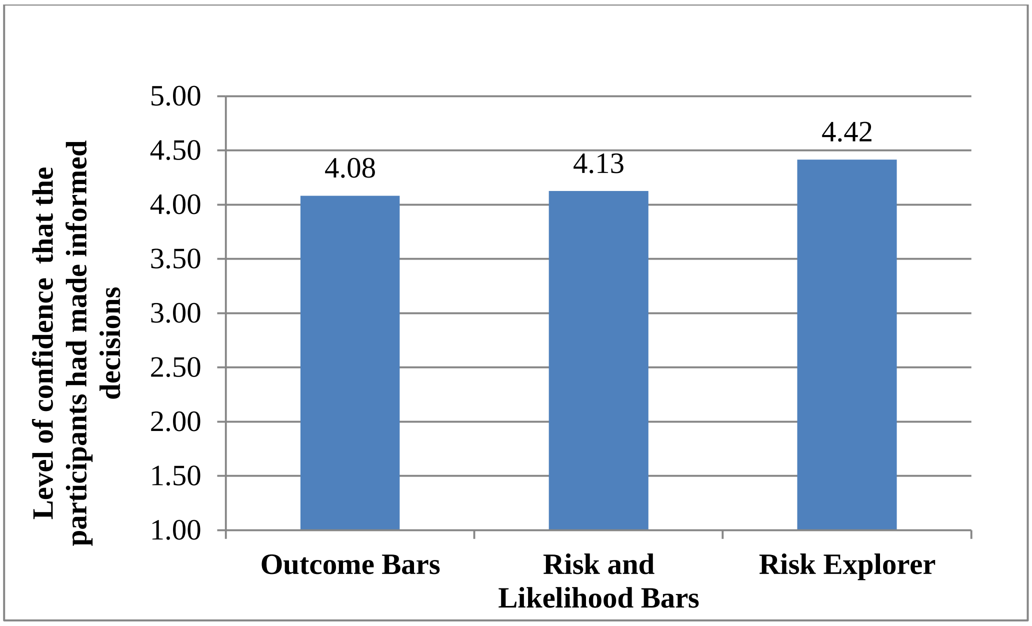


Figure 7.16: Average level of confidence that the participants had made informed decisions using each of the three interfaces of VisIDM

Although, on average, the participants’ level of confidence that they had made informed decisions increased when they moved from one interface to another, two of them showed a decrease in the level of confidence while using the Risk Explorer interface. Their level of confidence that they had made informed decisions dropped from 4 out of 5 (confident) to 2 out of 5 (low confidence). As stated by these participants, the Risk Explorer provided them with more information about the decision problem. Hence, they became more informed about the existence of many scenarios to consider and choose from so they became less confident about their choices. This is because on one hand, the scenarios used for comparing alternatives were not certain to occur and at the same time the other scenarios had the same probability of occurrence. Thus, an alternative that was considered the best under particular scenarios might not be the best under other scenarios. On the other hand, they were aware that the probability of making a loss or profit depends not only on the values that were fixed but also on the values of other variables. This result suggests that the availability of relevant information does not necessarily lead to an increase in the confidence that the decision made was informed. Rather, it is the ability of decision-makers to manipulate and employ this information that would enhance their confidence to make more informed decisions.

One participant justified his or her low level of confidence that they had made informed decisions when using the Risk Explorer interface by saying: *"Actually, although the data here is more comprehensive and gives an idea about all possible scenarios, but it was easy for me to determine which one is better using the previous interfaces. When I came to this interface I found myself confused about which one is better because I couldn't know how to compare between alternatives. Based on one scenario Alternative 4 is better than Alternative 2 but based on different scenario one alternative becomes better than the other. So I'm confused about which one is better. I think it depends on the scenarios you use for comparison."* The other participant commented: *"In the previous interface I had less variables to play with so I could know what is happening but here in this interface too much variables and values......Using the previous interfaces there is less chance to getting wrong, but here a lot of mechanics and solutions involved so became more complicated and thus confused about how to do the comparison."*

7.5.1 Main findings

The participants' responses on their level of confidence that they had made informed decisions led to the following findings:

- **A relatively high level of confidence**: on average, the participants showed a relatively high level of confidence that they had made informed decisions while using each of the three interfaces of VisIDM (see Figure 7.16).

- **An increase in the level of confidence**: most participants showed an increase in their confidence that they had informed decisions as they moved from one interface to another.

- **Availability of information vs. level of confidence**: the availability of information may not lead to increased confidence that the participants had made informed decisions. Rather, it is their ability to manipulate and employ information in decision-making that would enhance their confidence to make more informed decisions.

7.6 Adequacy of information provided

After completing all questions in each interface, the participants were asked to assess whether the information provided was adequate for making informed decisions. In addition, they were asked to state what types of information they would require to be better informed about the decision problem at hand.

The results summarised in Figure 7.17 show that only one participant stated that he had sufficient information to make an informed decision while using both interfaces of Outcome Bars and Risk and Likelihood Bars. In contrast, the number of participants who stated that they had sufficient information increased considerably to (10 out of 12) after using the Risk Explorer interface.

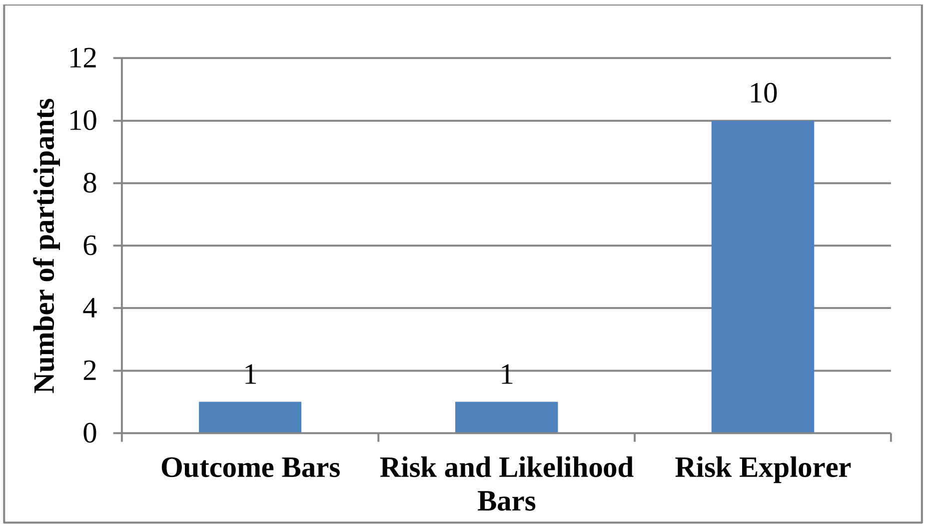


Figure 7.17: Number of participants who stated that they had sufficient information to make informed decision using each of the three interfaces of VisIDM

During the use of the three interfaces, the participants expressed a need for further information of different types. Figure 7.18 illustrates these types and the number of times each type was required by participants to feel more informed while using each interface of VisIDM. Although, they expressed the required types of information in different ways, they can be organised into three categories: 1) information about the inputs that made up the outcomes and risk associated with each alternative; 2) information related to the decision context, such as type of investment (e.g., whether the decision is to buy a house or restaurant); and 3) additional supporting information, such as statistical information (e.g., standard deviation). The following sections discuss the types of information requested by participants after using each of the three interfaces in more detail.

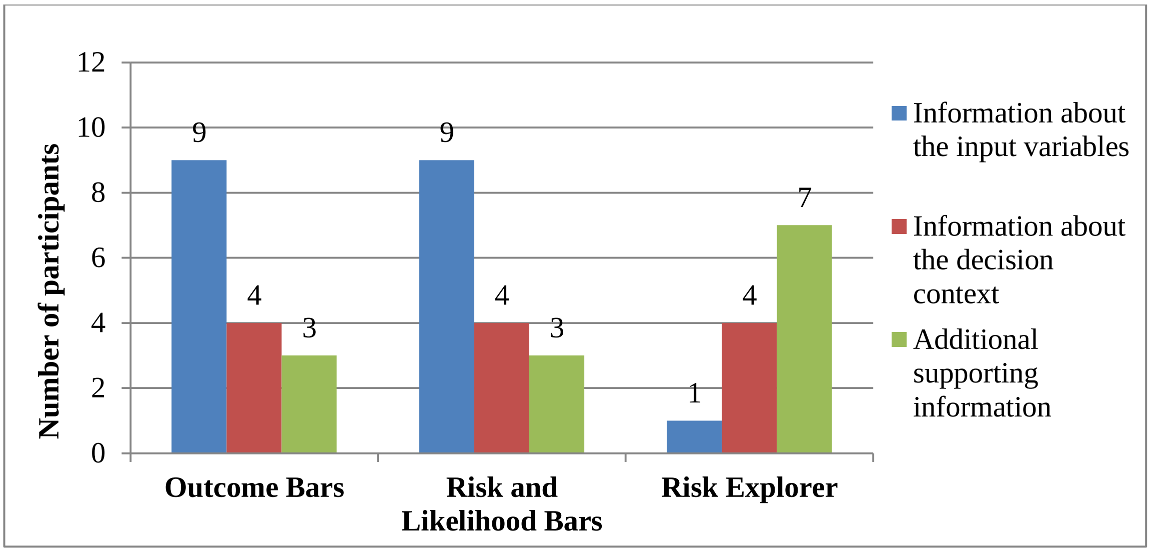


Figure 7.18: Types of information and frequency of stating a need for each type when using each of the three interfaces of VisIDM

7.6.1 Using both interfaces of Outcome Bars and Risk and Likelihood Bars

As shown in Figure 7.18, using both interfaces of Outcome Bars and Risk and Likelihood Bars, most participants (9 out of 12) stated that they need to be informed about the input variables that made up the range of outcomes and risk of making a loss associated with each alternative. Some of these participants stated that making decisions based on an overview of the range of outcomes and level of risk of making a loss associated with each alternative is not enough to be well-informed about the decision problem. For example, one participant commented: "*knowing the output and interpreting the risk is not enough. I need to know what factors that give these outputs.*" Generally, the participants identified a need for information related to the discount rate, cash inflows, initial investment, and time frame of each investment alternative. For example, the following extracts from the evaluations of participants 2, 4 and 6 respectively referred to this information:

"I want to see information related to Initial outlay of each investment."

"I would like to know the time frame of each investment (number of years)."

"Decision-making is not only about using NPV, there are many other factors (variables). For example, the discount rate, the payback of the business (inflow) also affects which investment to select. Also, how long the investment will be (no. of years)

and how much you will pay as salaries. I need information related to all kinds of cash flows, the cost, and the profit."

Some participants (4 out of 12) also stated a need to know more about the decision context; in other words, information that clarifies what type of decision they make and investment alternatives they choose from. One of these participants mentioned the importance of such information and the role it can play in the determination of the most preferred alternative. Another participant mentioned the relationship between the type of investment alternatives and her attitude toward the risk. This suggests that these participants preferred to respond on an emotional rather than rational basis. The following extracts from participants 4, 9 and 11 express their desire to have information related to the decision context and type of investments:

"I want to know about the decision context because things would change depends on the context."

"Having more information about decision context or type of projects will help me with what information I need because each context or type needs different information."

"I need to know what type of investment here. The type of investment, I mean the decision context is important. If I'm buying a house of course will be different than buying a vehicle because of the "value of investment". I mean if you want to buy a house or land the value of the investment will be increased in the future but if I'm buying a car the value of this investment will be depreciated in the future."

Some participants (3 out of 12) expressed a desire for additional supporting information to be more informed during the decision-making process. This included statistical information such as trends of outcomes and risk of making a loss and the standard deviation of outcomes. For example, one participant commented: *"In order to make an informed decision I still need further information such as the trends of the data and because I'm little bit thinking statistically, I like to know statistical information such as standard deviation and the external environment."* These participants also asked for information about the previous performance and history of each investment. For example, one participant commented: *"I think the information provided is not enough. I can give 70% to this information but I think 30% of the information I need could be related to the previous performance of the investments. I mean I need to know the history of each investment."* Although the Outcome Bars interface provides some useful statistical information such as distribution of outcomes, mean value and variation of outcomes, these comments indicates that it was difficult for these participants to integrate all this information for the purpose of reaching an informed decision. They also suggest that the VisIDM prototype should make such statistical information more salient and easier to obtain and utilise.

7.6.2 Using the Risk Explorer interface

When using the Risk Explorer interface, the majority of participants (10 out of 12) found most of the information they needed to be better informed (see Figure 7.17). It provided the participants with information related to the input variables that made up the outcomes and risk of making a loss and their ranges of values. It also provided the participants with detailed information related to the range of outcomes and risk associated with each alternative under many different scenarios (i.e. possible values of input variables). At the same time, the Risk Explorer interface enabled the participants to explore the relationships between the uncertainties in the input variables, risk of making a loss and the range of outcomes of each alternative. For all these reasons, the number of participants who stated a need for information related to the input variables that made up the outcomes and risk associated with each alternative dropped considerably from 9 to 1 out of 12 as shown in Figure 7.18. One participant for example commented: *“Here I can see the relationship between things. I mean the relationships between risk and the factors. It gives me more understanding about the risk.”*

However, the Risk Explorer interface did not provide further explanatory information about the decision context and type of alternatives (e.g., whether the decision is related to buying a house or restaurant). It also did not provide further detailed information about the components of the input variables (e.g., the components that constituted the cash outflows such as salaries and taxes). Therefore, the number of participants who expressed a desire for further explanatory information about the decision context stayed the same (4 out of 12) as it was during the use of both interfaces of Outcome Bars and Risk and Likelihood Bars. One participant commented: “*Decision type and the context help me to better understand the situation and may make me go with more risky option.*”

The number of participants who expressed a desire to have additional supporting information rose from 3 to 7 out of 12 during the use of the Risk Explorer interface (see Figure 7.18). It seems that while using the Risk Explorer interface, the participants gained knowledge and experience in the decision problem they dealt with and became more informed. Thus, they expressed a desire for additional supporting information for further analysis of the components that constituted the variables that made up the outcomes and risk associated with each of the alternatives. One participant commented: "*For now I'm ok with the information, but if I knew more details about the cash inflow and outflow, such as salaries and costs, it might be better to do more analysis."* Another participant commented: *"From the software, basically I have enough information to make my decision. However, having more variables and information will help me to make a better informed decision."*

7.6.3 Main findings

The participants' responses to the questions of whether the information provided was adequate to make informed decisions and what information they need to be more informed show that:

- **Adequacy of information provided**: most participants stated that there was a lack of adequate information to make informed decisions while using both interfaces of Outcome Bars and Risk and Likelihood Bars. However, they responded positively about the adequacy of information provided by VisIDM after using the Risk Explorer interface (see Figure 7.17).

- **Types of information needed to be more informed**: in addition to the range of outcomes and risk associated with each alternative, the participants stated a need for information related to: 1) the inputs that contribute to the outcomes and risk of making a loss; 2) the decision context and type of alternatives (e.g., whether the decision is to buy a house or restaurant); and 3) additional supporting information, such as statistical information.

CHAPTER 8
DISCUSSION

8.1 Introduction

This chapter discusses the results obtained from the study, which was designed to explore how the proposed VisIDM can assist people to make informed decisions under uncertainty and risk. It also discusses possible explanations and implications of these results and illustrates the limitations of the study.

The results presented in the previous chapter provide valuable insights into the usefulness of each feature of VisIDM for informed decision-making under uncertainty and risk. They allow us to shed light on how the participants utilised the given interactions and visual representations of information to arrive at their final decisions. They also reveal what types of information were used by participants to inform and justify their decisions and how VisIDM affected their perception and interpretation of the information presented.

8.2 Decision-making processes

The results of this study show that VisIDM can provide people with a variety of information and assist them in performing several operations to arrive at their final decisions. This is evident from the sequence of operations pursued and types of information used by participants in each interface of VisIDM. Examining these operations and information, we note that the participants adopted different strategies for decision-making. For example, to decide on whether one alternative is better than another, some participants compared them first based on the maximum NPV, which was interpreted as the maximum profit potential. Then, they further compared them based on the minimum NPV, which was interpreted as the maximum loss potential. At this point, they stopped searching for further cues and made their decisions based on the maximum and minimum NPV values. Other participants preferred to continue searching the visualisation interfaces for other information (e.g. proportions of positive and negative NPVs) and made decisions based on this information.

These results support the proposition that people rarely appraise and use all available information in a systematic way when making decisions under uncertainty and risk.

Rather, they often rely on simplistic modes of thinking (heuristics) to reduce the effort and processing required (Bekker *et al.*, 1999; Reynolds & Nelson, 2007; Tversky & Kahneman, 1974). Since heuristic decision processes depend on selected information, they can lead to cognitive bias, which in turn can lead to poorly informed decision-making (Kahneman & Frederick, 2005; Zacharakis & Shepherd, 2001). Bekker *et al.* (1999) propose that an informed decision is more likely to be achieved if people use systematic rather than heuristic information processing strategies. Future work could be focused on improving and examining the potential of VisIDM to guide users through a more systematic interpretation of the available information using rational choice models, such as Expected Utility Theory (EU) or the Theory of Bayesian Decision-Making.

The analysis of each participant's process for decision-making provides valuable insights into the benefits and drawbacks of each feature of VisIDM for informed decision-making under uncertainty and risk. The Outcome Bars interface was used by participants mainly to identify the extreme values of possible outcomes for each alternative. However, only a few used the probability distribution of these outcomes to inform their decisions. A possible explanation of this result is that some participants may not understand the significance of the distribution.

The Risk Bars that show the overall probability of undesirable outcomes were used by participants to compare alternatives and confirm the previous choices made using the Outcome Bars. This suggests that the Risk Bars are useful for conveying comparative information about the risk and people can understand the risk information when it is presented as percentages.

The Likelihood Bars that show the percentage at which an alternative would have the highest outcomes provide misleading information and don't facilitate informed decision-making. Half of the participants couldn't understand the concept and information conveyed by these bars. The other half interpreted the likelihood of an alternative having the highest outcome as the probability of making a profit. The Likelihood Bars could be eliminated from future versions of VisIDM and replaced by something easier to understand and use. For example, it could be a useful idea to replace the Likelihood Bars by bars that present information about the likelihood of obtaining desirable outcomes.

The Risk Explorer is useful for providing people with an overview of the risk associated with available alternatives through colour coding. At the same time, it facilitates the analysis and exploration of uncertainty and risk associated with alternatives at different levels of detail. The use of colour gradations to convey risk magnitudes can enable people to compare alternatives when they have different risk/return profiles. Also, it can be useful for attracting and holding people's attention, but it appears to discourage them from considering the numerical values of risk. However, it is not clear from the study if this affects the accurate assessment of the risk associated with alternatives or the validity of the eventual decision.

8.3 Risk awareness and perception

The results of this study suggest that VisIDM can raise people's awareness of the risk associated with available alternatives and assist them in analysing and exploring the two elements of risk (i.e. outcomes and probabilities) at different levels of detail. However, the results also show that people have problems in understanding and interpreting the uncertainty and risk information. In particular, they have a tendency to ignore the importance of probability information and rely, in large part, on the values of undesirable outcomes to form their impression about the risk.

Using the Outcome Bars interface, most participants did not use the probability distribution to evaluate the risk of undesirable outcomes associated with each alternative. Rather, they focused their attention on the minimum possible NPV, which represents the maximum potential loss. Consequently, they perceived the alternative with higher potential loss as more threatening than that with lower potential loss, regardless of probability. For example, most participants considered alternative 5 more risky than other alternatives because the maximum potential loss involved in alternative 5 is higher than that involved in other alternatives (refer to Section 7.2).

The same issue of risk perception was also observed when the participants used the Risk Explorer interface (refer to Section 7.4). In the Risk Explorer interface, the participants used two ways to identify and evaluate the risk of making a loss. Some made use of the red/green bars, which show the range of possible outcomes. Others identified and evaluated the risk by observing the colour variation across the cells of the grids. Interestingly, the majority of participants did not try to retrieve numerical values of the risk (i.e. the probability of making a loss), although they clearly understood how to do so in the practice phase of this study.

The literature on risk perception and decision-making suggests several possible explanations for the observed issue of risk perception; i.e. ignoring the importance of probability and relying on the outcomes to form the impression about the risk (refer to Section 2.3.2). Some of these explanations seem consistent with the observed risk perceptions of participants in this study. In the case of the Outcome Bars interface, it seems that the way of presenting information pertaining to the risk led to making the outcomes more prominent and easier to identify than their probabilities. Consequently, the participants focused their attention on the outcomes rather than their probabilities. This explanation seems consistent with previous research suggesting that prominent information is more likely to draw attention, be given more consideration, and have a stronger effect on risk-related behaviour than less prominent information (Stone *et al.*, 2003).

A second possible explanation for the observed issue of risk perception could be related to the attitude of the participants towards the risk. The majority of participants showed a preference for minimising the loss rather than maximising the profit. This might lead them to overestimate the risk involved in the alternatives with high potential loss. This bias in estimating the risk has been previously reported in the graphics perception literature, suggesting that people are poor at estimating "objective risk" (Stone *et al.*, 2003; Young & Oppenheimer, 2006). They have a tendency to perceive the low probability/high consequence outcomes as more risky than high probability/lower consequence outcomes (Schwartz & Hasnain, 2002; Weber & Milliman, 1997).

8.4 Level of confidence that the participants had made informed decisions

The results show that the participants' level of confidence that they had made informed decisions was generally high when using the three interfaces of VisIDM (see Figure 7.16). In addition, most participants showed an increase in their confidence that they had made informed decisions as they moved from one interface to another. This suggests that the participants believed that they were able to understand and exploit the information provided in each of the three interfaces. It also suggests that as the participants moved from one interface to another, they felt more informed because of the new information they perceived and their ability to use this information in decision-making.

Interestingly, two of the 12 participants showed a decrease in their level of confidence while using the Risk Explorer interface, despite their positive responses to the adequacy of information. This suggests that the additional information offered by Risk Explorer made these participants consider additional options which in turn made them less certain of their final choice. For example, one participant commented: *"Using the previous interfaces there is less chance to getting wrong, but here a lot of mechanics and solutions involved so became more complicated."* The other participant commented: *"Actually, although the data here is more comprehensive and gives an idea about all possible scenarios, but it was easy for me to determine which one is better using the previous interfaces."* These comments suggest that the participants find it easier to make a choice among a small number of possibilities. The danger of course is that the missing scenarios may be the most advantageous. Ease of choice does not result in the best choices.

The results also show that most participants reported a high level of confidence that their decisions were well informed while using the Outcome Bars and Risk and Likelihood Bars (see Figure 7.16). In contrast, they stated a lack of sufficient information for making informed decisions while using these interfaces (see Figure 7.17). This raises a question about the objectivity of the participants in their evaluation of the level of confidence that they had made informed decisions. One possible explanation is that the participants may have overestimated their level of confidence that they had made informed decisions. According to Arnott (2006), the confidence bias acts to increase an individual's confidence in his or her ability as a decision-maker. Both professional and laypeople are subject to this bias (Christensen-Szalanski & Bushyhead, 1981; McNeil *et al.*, 1982).

Two types of bias that might affect the participants' evaluation of their level of confidence were observed, as illustrated below:

- Confirmation bias: It was observed that some participants tried to seek confirming rather than disconfirming information. Once they had chosen one alternative, they proceeded to search the visualisation interfaces in a selective manner for confirming information. As a result of finding confirming information, they developed high confidence that their original choice was informed. For example, some participants who considered alternative 4 as the best alternative because of the low risk of making a loss tried to confirm their choice by seeking information and scenarios that demonstrated that alternative 4 involved lower risk of making a loss compared to other alternatives. Once they found evidence, they felt highly confident that they had sufficient information to be adequately informed. Several studies have addressed the effect of confirmation bias on making informed decisions. For example, Kahneman & Frederick (2005) suggest that confirmation bias leads to placing greater weight on information confirming the prior choices and expectations than on contradictory evidence, which in turn can lead to poorly informed and irrational decisions.

- Overconfidence bias: some participants showed overconfidence in their ability to make decisions and solve difficult financial problems. This was reflected in their high level of confidence that they had made informed decisions. For example, one participant expressed his or her confidence using the ‘Outcome Bars’ by saying: “*I’m very confident that I was well informed, it’s easy*.” However, this participant expressed a lack of sufficient information to make an informed decision. There is substantial evidence from the judgment and decision-making literature that suggests that the overconfidence bias affects how information is obtained and processed in order to make informed decision (see for example, Fischhoff *et al.*, 1977; Oskamp, 1965; Zacharakis & Shepherd, 2001). Grichnik (2008) proposes that an overconfident person handles postulated assumptions as facts. Thus, the overconfidence bias influences risk perception to an extent that the decision-maker may fail as a result of his or her wrong assessment of the risk.

Although cognitive biases are inherent in human reasoning and decision-making, they could be reduced by incorporating “debiasing” procedures into the development process of InfoVis tools to support decision-making. Arnott (2006) proposes a debiasing approach that can be considered in the design of user interfaces of decision support systems. The steps in this procedure are: 1) identification of the existence and nature of potential biases; 2) identification of the likely impact and the magnitude of potential biases; and 3) consideration of ways and techniques to reduce or eliminate the effect of potential biases. Tsai *et al.*(2011) propose that the effect of decision biases could be reduced or eliminated by using formal decision analysis methods and creating visualisations that can naturally guide people and nudge them towards reasoning in a Bayesian manner.

8.5 Adequacy of information to make informed decisions

The results show that most participants eventually responded positively in relation to the adequacy of information provided by VisIDM after using the Risk Explorer interface (see Figure 7.17). This suggests that VisIDM provided them with most of the information they considered necessary to feel well-informed.

Nevertheless, while working through the tasks, the participants commented about different types of information that they might require. In addition to the range of possible outcomes and risk of making a loss, the participants asked for information related to: 1) the inputs that contribute to the outcomes and risk of making a loss associated with each alternative; 2) the decision context and type of alternatives (e.g., whether the decision is to buy a house or restaurant); and 3) additional supporting information, such as statistical information. For example, one participant commented: "*Decision type and the context help me to better understand the situation and may make me go with more risky option.*" In a real-world scenario of decision-making, however, people are usually aware of the decision context and are able to set up the uncertainties and criteria on which decisions are based. It would be useful to assess the utility of VisIDM in real settings and see how the participants' performance and decisions would differ from hypothetical situations.

Using the Outcome Bars and Risk and Likelihood Bars, the majority of participants asked for information about the input variables that contribute to the outcomes and risk of making a loss associated with each alternative. This result suggests that the participants were not satisfied to rely solely on the outcomes and their probabilities to make informed decisions. It also suggests that they need to have more control over the input uncertainties, which they would do in a real situation. Since VisIDM, through the Risk Explorer interface, provides information related to the input variables, the proportion of participants who expressed a desire for further information related to the input variables dropped from 9 to 1 out of 12.

Some participants (4 out of 12) asked for explanatory information about the decision context, such as the type of decision (e.g., whether the decision is to buy a house or restaurant). This result suggests that these participants preferred to respond on an emotional rather than rational basis, and to base their decisions on the context rather than the content of information (Bekker *et al.*, 1999). Some participants (3 out of 12) also asked for some statistical information (e.g., standard deviation of outcomes and their trends). Although VisIDM provides some useful statistical information such as distribution of outcomes, mean value and variation of outcomes and risk values, it seems that it was difficult for these participants to integrate all this information for the purpose of reaching an informed decision.

8.6 Study limitations

There were several limitations to this study that should be considered in the interpretation of the results. Firstly, a specific group of participants were recruited, namely postgraduate students from the Faculty of Commerce. Considering their majors, the participating students most likely had higher numerical skills than average. Hence, the participants' characteristics may not reflect the diversity of actual decision-makers. However, this limitation makes the results all the more interesting. For example, even those who should be equipped to accurately understand risk information had trouble with risk perception and did not pay appropriate attention to the probability of outcomes in determining the risk.

Secondly, the results are limited by the lack of variability in participants' preferences. Contrary to expectations, the great majority of participants in this study showed a preference to minimise the potential loss rather than maximise the gain. Hence, it is not clear if the results and decision-making processes described above would hold true with other participants who would have different preferences.

Finally, the results are limited by the hypothetical nature of the decision problem. In this study the participants were presented with a decision-making scenario with only five investment alternatives. Hence, the results cannot confirm whether participants considered all factors that would be relevant to a real decision, nor whether their decisions in the hypothetical situation would reflect their actions in a real-world setting. However, the main aim of the study is to develop insights and understanding about the usefulness of VisIDM rather than to compare how people's decisions in hypothetical situations are different from real settings. Since the study was successful in showing the benefits and drawbacks of VisIDM, the results might help other InfoVis researchers who aim to support similar decision-making scenarios. These could be found in healthcare decision-making, consumer decision-making, managerial decision-making and other domains.

CHAPTER 9
CONCLUSIONS

This chapter summarises the research conducted in this thesis and presents the main conclusions drawn from it. It also presents the main contributions made by the thesis and concludes with a discussion of possible directions for future research.

9.1 Summary

Decision-making is a human activity, but one which can and should be supported by access to appropriate information and by using technology to help distil that information. One technology that is emerging as a useful support to informed decision-making is information visualisation. It can support informed decision-making by portraying information in ways that make it amenable to analysis and exploration. It can facilitate the integration of uncertainty into the decision-making process, and raise the awareness of decision-makers about its consequences. Moreover, it can enhance the ability of decision-makers to manipulate and comprehend information, thereby making more informed decisions.

The main objective of this thesis was to develop a new InfoVis tool and explore its usefulness for assisting people to make informed decisions in the presence of uncertainty and risk. This objective was translated into the following research question:

How can InfoVis tools assist people to make informed decisions under uncertainty and risk?

To achieve the objective of this thesis, the literature on decision-making under uncertainty and risk was reviewed. This review provided us with background and insight into the information requirements and main considerations that constitute the basis for the design and evaluation of the InfoVis tools presented in this thesis. Two main considerations were identified through the literature review. Firstly, in the presence of uncertainty and risk, reasoned decisions cannot be judged as right or wrong. Rather, reasoned decisions are those that are well-informed and consistent with the decision-maker’s objectives and preferences. Secondly, to enable informed decision-making, the uncertainty should be treated from the beginning of the decision-making process as an integral part of the information on which decisions are based. Our approach for making uncertainty an integral part is to view the whole process as one of determining the risk associated with making the decision.

Based on the design considerations and information requirements identified through the literature review, an InfoVis tool to support informed decision-making under uncertainty and risk (VisIDM) was designed and implemented. VisIDM consists of two main parts: the Decision Bars and Risk Explorer. Decision Bars provide overview information of the decision problem and available alternatives through three panels: Outcome, Risk and Likelihood Bars. Using these bars, decision-makers can compare and then choose preferred alternatives before focusing on particular alternatives for detailed analysis and exploration. In contrast, Risk Explorer provides decision-makers with a multivariate representation of uncertainty and risk associated with the decision alternatives. Using Risk Explorer, decision-makers can interactively analyse and explore the available alternatives, either consecutively or simultaneously, at different levels of detail.

After the design and implementation of VisIDM, a study that utilised a qualitative approach was designed and conducted to assess the ability of VisIDM to assist people to make informed decisions under uncertainty and risk. The study also investigated how the proposed VisIDM was used by participants and what features supported their exploration and perception of information. Twelve postgraduate students from the Faculty of Commerce at Lincoln University were recruited in this study. They were given a decision-making scenario and asked a number of questions where they had to make decisions taking into consideration the uncertainty and risk associated with the information available.

The results of this study leads to several interesting conclusions. However, it is noteworthy to mention that these conclusions are limited to this study and may not be generalised since the participants are not reflective of the population as a whole. The main conclusions drawn from the results of this study can be summarised as follows:

- VisIDM is a useful tool for assisting people to make informed decisions under uncertainty and risk. It provides people with a variety of decision-relevant information and assists them in performing several tasks to arrive at their final decisions. It also makes people aware of the uncertainty and risk associated with decision-making and facilitates their analysis and exploration at different levels of detail.

- Although different types of information that people may need to make their decisions are presented in VisIDM, people tend to rely on a single or small number of salient pieces of information rather than on a systematic consideration and evaluation of all available information.

- Having an accurate understanding of the two elements of risk (i.e. outcome and probabilities) is a key element of an informed decision. However, people have a tendency to use the perceived consequences of undesirable outcomes to form their impressions about the risk, with the probability of these outcomes playing a small role.

- The availability of additional information may not contribute greatly to people's feeling of increased confidence that they can make informed decisions. However, their ability to comprehend and manipulate information would enhance their confidence to make informed decisions.

- The availability of information related to the possible outcomes and their likelihoods for each available alternative could be insufficient to enable informed decision-making. People feel more comfortable if they have control over the input uncertainties that contribute to these outcomes and explanatory information related to the decision context and types of alternatives.

9.2 Contributions

The main contributions made by this thesis can be summarised as follows:

- An analysis and exploration of information requirements and considerations that need to be taken into account when designing InfoVis tools to support informed decision-making under uncertainty and risk. While these information requirements and design considerations still need further exploration, we believe that they serve as guidelines for further research to build upon. The detailed discussion of these information requirements and design considerations is provided in Chapter 4.

- The design and implementation of a new interactive InfoVis tool to present information on the decision problem and to facilitate its analysis and exploration at different granularities of detail called VisIDM. The major innovation in this tool is the inclusion of information about the uncertainty and risk involved in the decision. The detailed description of VisIDM is provided in Chapter 5.

- A qualitative evaluation of the ability and usefulness of VisIDM for assisting people to make informed decisions under uncertainty and risk. This evaluation allows us to shed light on how users utilise the given interactions and visual presentations of information of VisIDM to arrive at their final decisions. It also reveals what types of information users use to inform and justify their decisions and how VisIDM affects their understanding and interpretation of information presented. The evaluation study is described in detail in Chapter 6 and the results obtained are presented and discussed in Chapters 7 and 8.

9.3 Future research directions

There are several directions for research that can be built upon the work presented in this thesis. Future research can be split into: enhancing the proposed VisIDM, further evaluation, and applying VisIDM to other decision making scenarios.

9.3.1 Enhancing the proposed VisIDM

One possible extension to this work would be enhancing the design of some features of VisIDM, so that it provides decision-makers with a better understanding of uncertainties and risks associated with decision-making. As discussed in the previous chapter, some design and usability issues arose through the evaluation study: difficult to use features, difficult concepts and terminologies, and hidden algorithms to calculate the outcomes and risk associated with alternatives. To resolve these issues, the current VisIDM could be updated as follows.

First, some participants found it difficult to make use of probability distribution information. Hence, it could be improved so that it provides probability information in a clearer and more informative format. Some alternative formats for portraying the probability information are also available in the literature on risk visualisation. For example, cumulative distribution functions, histograms, and boxplots can show different types of information that people usually seek for decision-making purposes (Gresh *et al.*, 2011). It would be useful to explore whether these formats can provide probability information in a more intuitive way. Perhaps, though, there is a need to develop much more innovative approaches to conveying probability information.

Second, as the Likelihood Bars are difficult to understand and provide misleading information, they could be eliminated or replaced by bars that show the probability of obtaining desirable outcomes (e.g., the probability of making a profit in an investment decision-making scenario). This would allow VisIDM to provide more balanced presentation of potential risks and benefits of available alternatives, thus allowing decision-makers to make better informed decisions.

Third, additional visual and computational features could be added to allow the decision-maker to control the process of generating outcomes and risk information and their integration into the decision-making process. For example, it would be useful to explore the consequences of allowing the decision-maker to modify the model parameters and their potential uncertain values, specify thresholds at which the risk is acceptable or not, and incorporate his/her risk preferences into the analysis and decision-making process.

Another possible extension to this work would be improving VisIDM, so that it is able to deal with different types of uncertainty and different methods of uncertainty representation. This work deals with the uncertainty associated with input variables and model outcomes represented as a range of values that is bounded by minimum and maximum values. In reality, however, decision-making problems are affected by uncertainty arising from different sources. For example, it is common to have uncertainty in the criteria weights and models used in decision-making. Such uncertainties require different methods for modelling and representations due to their nature and characteristics. The literature on decision-making offers several methods to represent and model the amount and nature of uncertainty such as possibility theory, belief functions, fuzzy sets and Dempster-Shafer Theory of Evidence (Streit, 2008). Future work could be devoted to improve the interface and computational facilities of VisIDM so that it can provide better integration of different types of uncertainty into the proposed VisIDM.

Another area of improvement would be to explore several of theheuristics that describe how people actually make decisions (for a review see, for example, Shah & Oppenheimer, 2008), and provide additional visualisation techniques to support these heuristics. Future work could also focus on investigating the ability of integrating rational decision-making models such as the Subjective Expected Utility theory or Bayesian decision-making theory into VisIDM. If a rational model is integrated into VisIDM, would it be able to provide better support for informed decision-making under uncertainty and risk? Would VisIDM serve as a debiasing approach and guide users through a systematic and balanced evaluation of the available information when making decisions under uncertainty and risk?

9.3.2 Further evaluation

In spite of its limitations, the current study provides us with understanding on how VisIDM can be used by participants to arrive at their final decisions and what features effectively support their exploration of information. The study also indicates that our approach of including the risk of making an acceptable decision as an integral part of the decision-making process could have significant merit. However, more evaluation studies are needed to provide more evidence of the usefulness of VisIDM to support informed decision-making under uncertainty and risk. These studies should be expanded beyond hypothetical decision-making scenarios and lab-based environment to real world settings. They should also be expanded to include different measures and factors related to informed decision-making such as measures of beliefs, attitudes, perception of risk, and knowledge (Bekker *et al.*, 1999).

9.3.3 Applying VisIDM to other decision-making scenarios

Another direction that would be fruitful would be developing the concepts embodied in VisIDM, so that they can be applied in other decision-making scenarios. In the scenario of investment decision-making used to assess VisIDM in this study, participants described themselves as risk-averse. This attitude might lead them to search and use information in a selective manner and to overestimate the risk involved in the alternatives with high potential loss. If VisIDM is further improved and applied in other scenarios of decision-making with other participants who would have different preferences, the advantages of using the approach embodied in VisIDM to support informed decision-making under uncertainty and risk could be more pronounced. For example, it would be useful to improve and apply these concepts to the domain of medical decision-making, which is full of uncertainties and risks that need to be communicated to patients.

Future research could also move beyond visualisation of numerical information and explore other data types such as categorical data. Uncertainty in non-numerical information is commonplace in many decision-making scenarios, such as the soil types and vegetation types in environmental decision-making and potential side effects of drugs in medical diagnosis. The representation, utilisation and integration of such uncertainties into decision-making present their own sets of challenges. If an InfoVis tool to deal with non-numerical information and its associated uncertainty in decision-making is developed, it will be applicable to a variety of domains.

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APPENDIX A

A.1 Material of the pilot study (Chapter 5, Section 5.4)

This is the material of the pilot study that was conducted to assess the efficacy of Interactive Tornado Diagram and Risk Explorer prototypes.

Entrance Questionnaire

Please Rate your experience in the following areas:

- **Financial Modeling.** (e.g. Net Present Value)

☐ None ☐ Beginner ☐ Intermediate ☐ Advanced

- **Decision Making under Uncertainty.**

☐ None ☐ Beginner ☐ Intermediate ☐ Advanced

- **Risk Assessment.**

☐ None ☐ Beginner ☐ Intermediate ☐ Advanced

Description of the InfoVis prototypes

Interactive Tornado Diagram

Figure 1 shows the likely ranges of Net Present Value (NPV) resulting from different ranges of the input variables: Initial Investment, Cash Inflow, Cash Outflow, Discount Rate, and Years of investment over a specified range of values. All of the input variables are bounded by a known maximum and minimum, and all values in between occur with equal likelihood. Each horizontal bar represents the range of NPV as the related variable is varied within its specified range while the other variables remain constant at their current values.

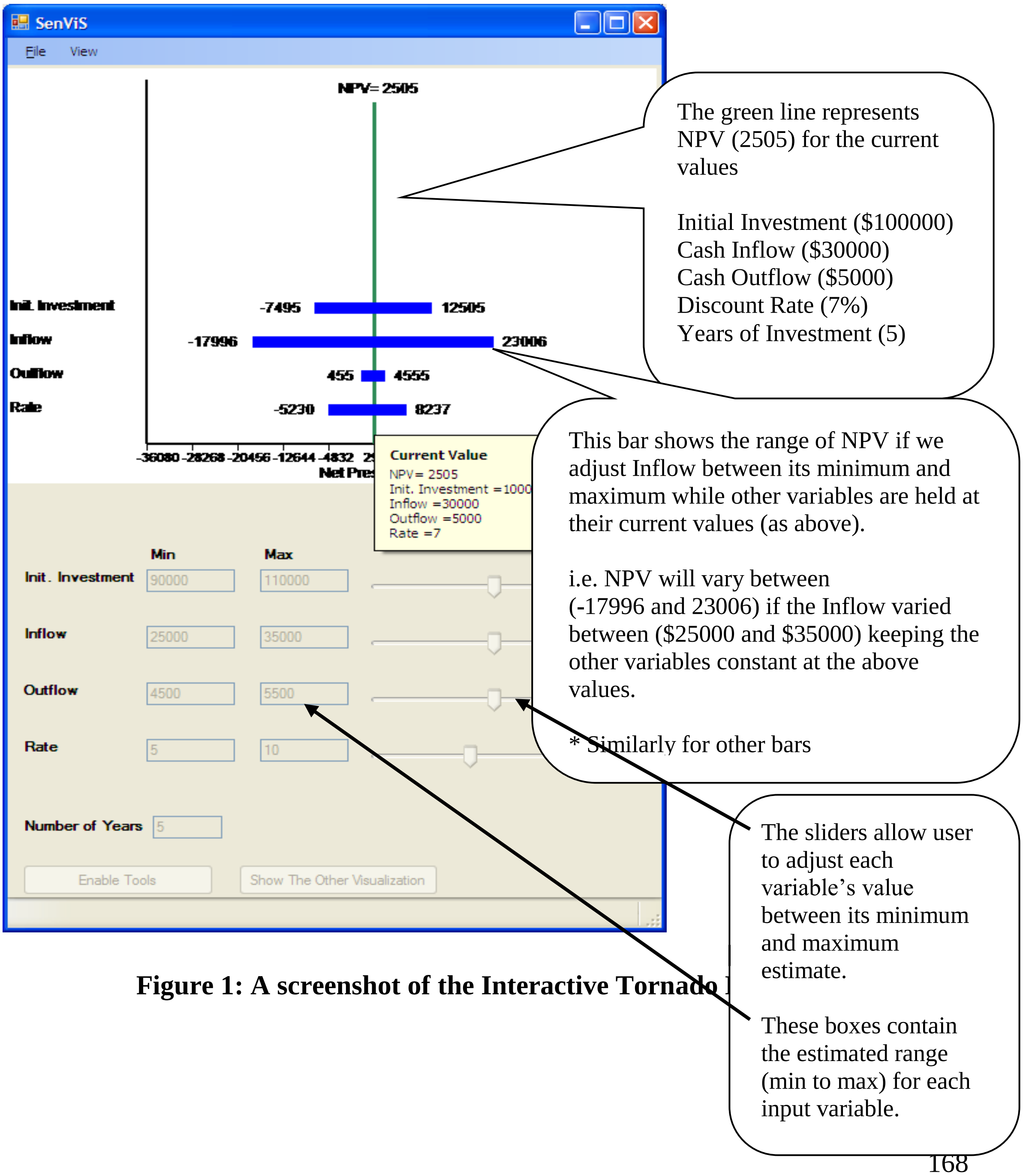

Figure 1: A screenshot of the Interactive Tornado

Risk Explorer

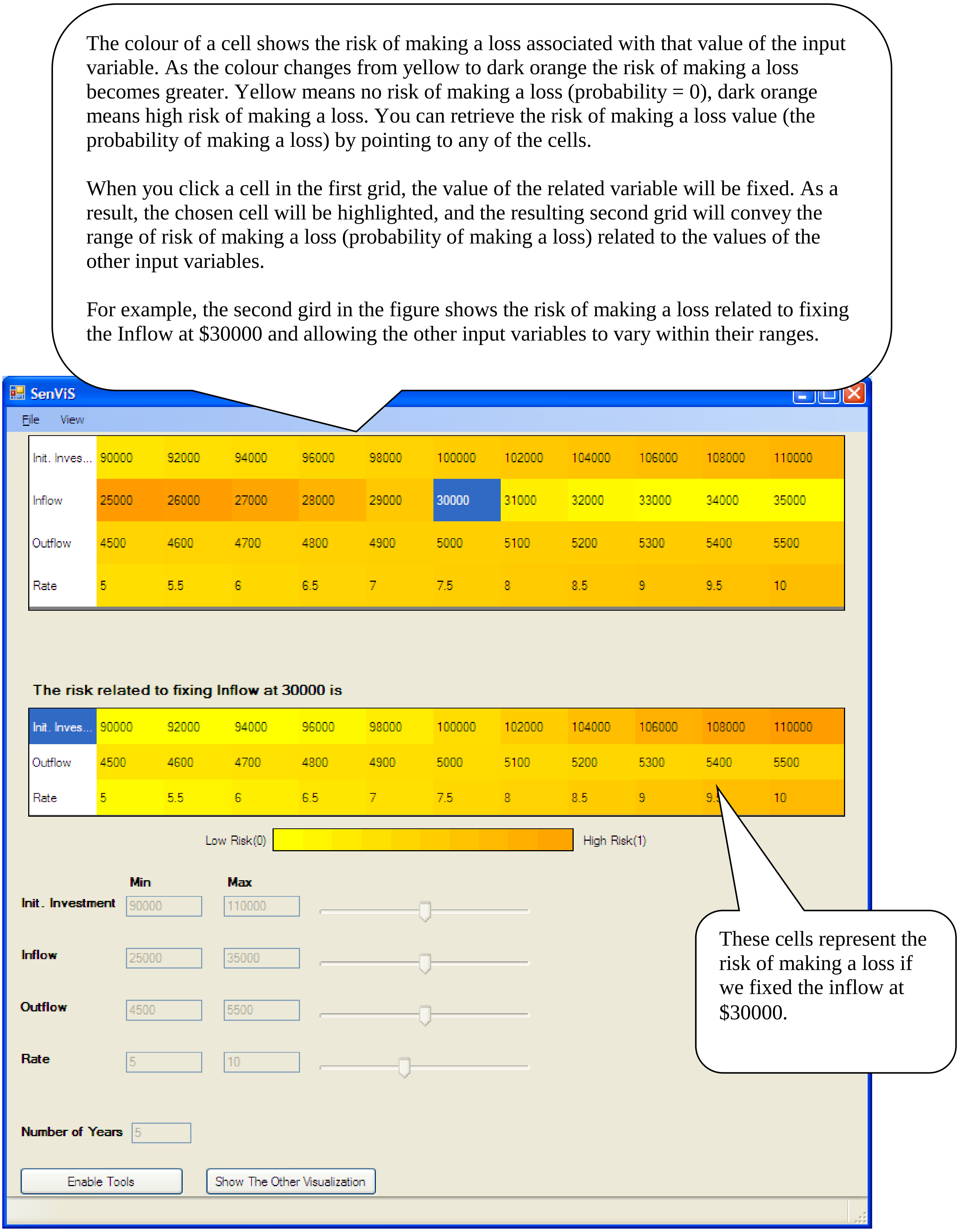

Figure 2: A screenshot of the Risk Explorer prototype.

Description of the decision-making scenario

"*You are planning to make an investment and you need to make a decision based on the value of the NPV. You are uncertain about the exact values of the model's input variables so there is a risk involved in your decision. You need to deal with this uncertainty and assess the risk of your decision. The risk here means the probability of making a loss.*"

The current values for the input variables displayed in the diagram are:

Initial Investment	$100000,
Cash Inflow	$30000,
Cash Outflow	$5000
Discount Rate	7%
Time	5 years.

Tasks given to participants

Based on the displayed ranges of the input variables, try to answer the same questions.

1. For the displayed ranges, which variable do you think has the most effect on the risk of making a loss?

☐ Initial Investment ☐ Inflow ☐ Outflow ☐ Rate

Rate the easiness a. Very easy b. Moderately easy c. Difficult d. Very difficult

2. Approximately, for what range of cash inflow can you be assured that the NPV will stay > 0 i.e. there is no risk of making a loss? (Other input variables can vary within their ranges).

☐$25000 - $35000 ☐$28000 - $35000 ☐$29000 - $35000 ☐$33000 - $35000

Rate the easiness a. Very easy b. Moderately easy c. Difficult d. Very difficult

3. What do you think the risk of making a loss will be if the Discount rate becomes 10%? (Other input variables can vary within their ranges).

☐ 0.155 ☐ 0.245 ☐ 0.355 ☐ 0.565 ☐ 0.656

Rate the easiness a. Very easy b. Moderately easy c. Difficult d. Very difficult

4. **Given that Initial investment is fixed at $90000, what is the minimum Cash Inflow that will ensure a positive NPV? i.e. probability of making a loss is zero. (Other input variables can vary within their ranges).**

☐$25000 ☐$29000 ☐$29400 ☐$30000

Rate the easiness a. Very easy b. Moderately easy c. Difficult d. Very difficult

5. **If the Inflow is $30000, what is the range of rate values that will ensure low risk of making a loss? (Other input variables can vary within their ranges).**

☐5% - 6.5% ☐7% - 8% ☐8.5% - 9% ☐9% - 10%

Rate the easiness a. Very easy b. Moderately easy c. Difficult d. Very difficult

6. **On a scale of 1--5 (1= not confident to 5= highly confident), would the prototype support you in making a confident investment decision in the situations above?**

A.2 Results of the pilot study (Chapter 5, Section 5.4)

Accuracy

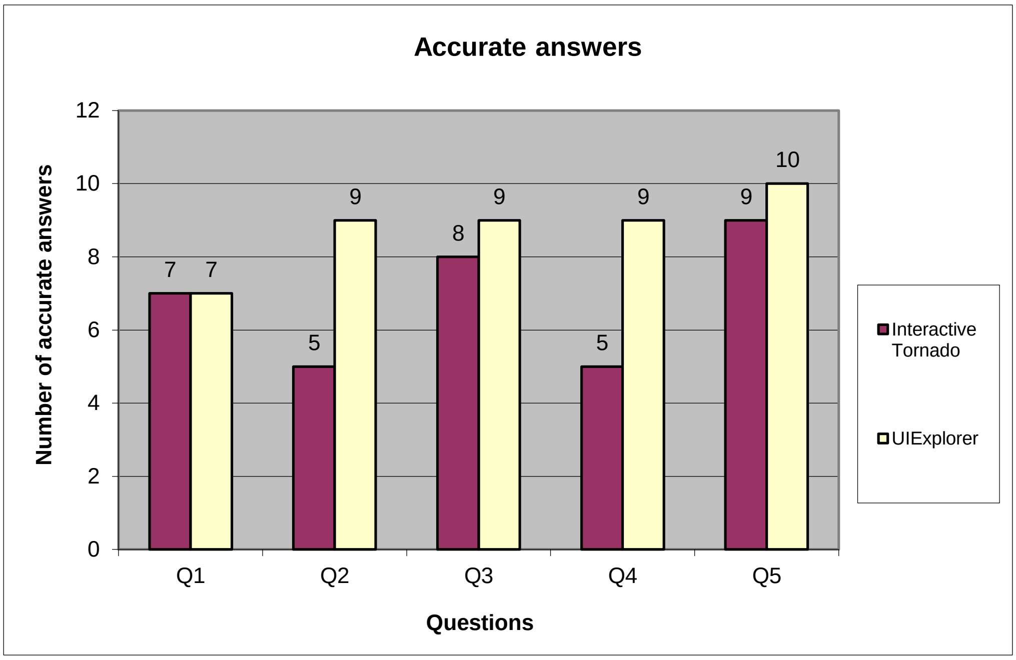

Figure 3: Comparison between the two visualisations in terms of accuracy.

Time Taken

Table 1: Summary of the time taken Results

Visualisation prototype	Average	Stddev	Min	Max
Interactive Tornado	6.2	1.32	5	9
Risk Explorer	6	1.15	5	8

Ease of Use

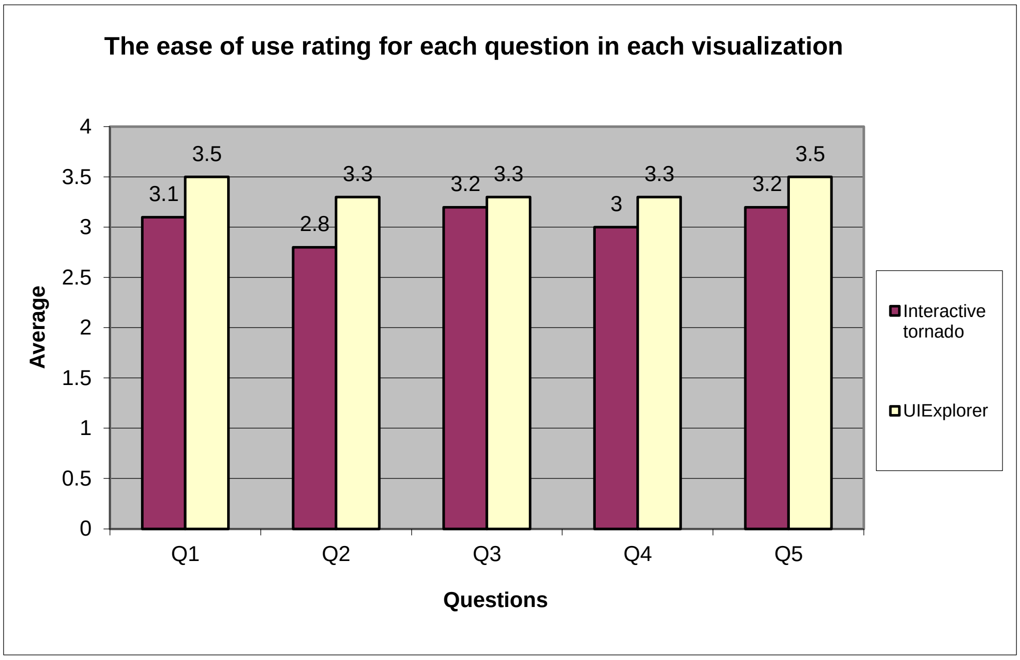

Figure 4: Comparison between the ease of use for each question in each visualisation.

Level of Confidence

Table 3 : confidence level results.

Visualisation prototype	Average	Stddev	Min	Max
Interactive Tornado	3.7	0.82	2	5
Risk Explorer	4.3	0.94	2	5

APPENDIX B

B.1 Material of the evaluation study (Chapter 6)

This is the material of the evaluation study that was conducted to assess the ability and usefulness of the VisIDM prototype in supporting informed decision-making under risk and uncertainty.

Introduction

In this user trial, you will evaluate a visualisation tool designed to support decision-making in the presence of uncertainty and risk. The trial presents three versions of the visualisation tool. Each version adds more information to the previous version.

The case study we are visualising here is a decision problem consisting of five decision alternatives (Alt1, Alt2, Alt3, Alt4 and Alt5). Because all the alternatives involve the investment of dollars, the Net Present Value (NPV) model is used for the evaluation and comparison of alternatives. NPV is a financial model used to analyse the profitability of an investment or project. A positive NPV indicates that the investment is profitable, while a negative NPV indicates that the investment is making a loss.

There is uncertainty in the values of the NPV's input variables (e.g. uncertainty in the Discount Rate). Consequently, each alternative has a range of possible NPVs and involves a certain amount of risk.

The trial requires you to read the description of each version of the visualisation tool and complete the tasks listed after the description of each version.

Consent Form

Consent Form for Requirements and/or Software Evaluation

Name of Project: Information Visualisation to Support Informed Decision-Making under Uncertainty and Risk

I have read and understood the research information sheet for the above-named project. On this basis I agree to participate as a subject in the project, and I consent to publication of the results of the project with the understanding that anonymity will be preserved. I understand also that I may at any time withdraw from the project, including withdrawal of any information I have provided.

I confirm that I am over 16 years of age.

Name: ______________________________

Signed: ______________________________ Date: __________

Ethical Approval for Research in Software Design and Evaluation

Ethics Approval for Research in Software Design and Evaluation
Please fill in this form to apply for ethics approval for user requirement surveys and software evaluation via Lincoln University's ethics approval for:
Generic Approval for Research in Software Design and Evaluation in the Applied Computing Group (2007-66)

Please attach copies of questionnaires, information and consent forms based on the templates at the end of this document.

Date:	15th June 2010
Student's Name:	Mohammad Daradkeh
Supervisor(s):	Dr. Clare Churcher & Prof. Alan McKinnon
Degree:	PhD
Title of thesis:	**Information Visualisation to Support Informed Decision-Making under Uncertainty and Risk.**
Brief Description:	The purpose of this experiment is to evaluate the efficacy of visualisation tools designed for decision-making support under conditions of uncertainty and risk. We are testing the tools to see if they could support decision makers in performing decision-making and analysis tasks in the presence of uncertainty and risk. The experiment will be run in 20 individual 50-minutes sessions. Each individual session will consist of a short pre-study questionnaire, a set of tasks and an interview/debriefing session. The individual participants complete the tasks while being observed. Data will be collected through the use of a "thinking aloud" protocol and audio recording for each of the participants.

Approval is given for this trial:

Head of Applied Computing Dept. *Dr. Keith Unsworth*

Contact Details: *keith.unsworth@lincoln.ac.nz*

Date: *15/June/2010*

Department of Applied Computing
Faculty of Environment Society & Design
PO Box 84
Lincoln University
Lincoln 7647
Canterbury, New Zealand

Dataset used in the implementation of VisIDM and evaluation study

Alt1

5

Init. Investment,38000,30000,40000

Inflow,12500,10000,15000

Outflow,5000,4500,5100

Discount Rate,7,5,10

Alt2

5

Init. Investment,30050,29000,35000

Inflow,20000,15000,22000

Outflow,7500,7000,8000

Discount Rate,7,5,10

Alt3

5

Init. Investment,31000,29500,33000

Inflow,18000,15000,20000

Outflow,9000,8000,10000

Discount Rate,7,5,10

Alt4

5

Init. Investment,36300,35300,40000

Inflow,22000,20000,25000

Outflow,10000,9000,11000

Discount Rate,7,5,10

Alt5

5

Init. Investment,42000,35000,45000

Inflow,28000,25000,30000

Outflow,15000,10000,20000

Discount Rate,9,5,10

Background Questionnaire

Please rate your experience with each of the following areas by placing a check in the appropriate box

1. How do you rate your experience with financial models (e.g. Net Present Value):

   ☐ None.

   ☐ Have learned and understand the concepts.

   ☐ Have practiced them regularly through study and/or work.

2. How do you rate your experience with decision-making under certainty, where all decision variables/parameters are known deterministically and each decision alternative has only one possible outcome:

   ☐ This is my first time.

   ☐ Basic understanding of decision-making concepts.

   ☐ Regularly practice decision-making and analysis methods and techniques.

3. How do you rate your experience with decision-making under conditions of uncertainty and risk, where there is uncertainty in the values of decision variables/parameters and hence every decision alternative has various possible outcomes and involves a certain amount of risk:

   ☐ This is my first time.

   ☐ Basic understanding of concepts of decision-making under uncertainty and risk.

   ☐ Regularly practice decision making and analysis under uncertainty and risk.

The first version of the visualisation tool

Figure 1 shows a screenshot of the first version of the visualisation tool. Please read the description in Figure 1 and then complete the following tasks.

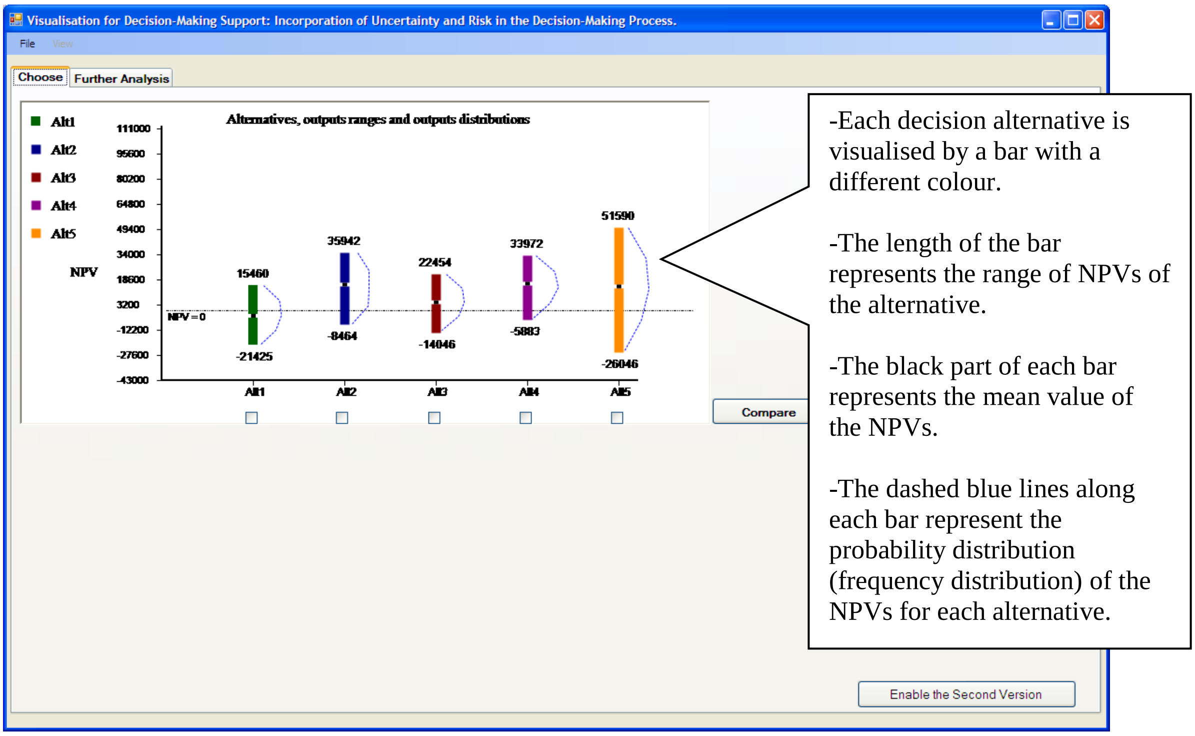

Figure 1: A screenshot of the first version of the visualisation tool.

Practice Tasks

1. Which alternative has the greatest range of NPVs?

   ☐ Alt1 ☐ Alt2 ☐ Alt3 ☐ Alt4 ☐ Alt5

2. Which alternative has the maximum possible NPV?

   ☐ Alt1 ☐ Alt2 ☐ Alt3 ☐ Alt4 ☐ Alt5

3. Which alternative has the minimum possible NPV?

   ☐ Alt1 ☐ Alt2 ☐ Alt3 ☐ Alt4 ☐ Alt5

4. For Alt4 most of the possible values of NPV are:

   ☐ Slightly skewed to the minimum NPV ☐ Slightly skewed to the maximum NPV ☐ Clustered around the mean value ☐ Evenly distributed

5. What are the top two alternatives according to the mean value of NPVs?

   ☐ Alt2 Alt4 ☐ Alt2 Alt5 ☐ Alt1 Alt5 ☐ Alt3 Alt4

Decision-Making Scenario:

Please read through the following scenario then complete the following tasks:

“Suppose you are planning to make an investment and you have five alternatives to choose from: Alt1, Alt2, Alt3, Alt4 and Alt5. Because they all involve the investment of dollars, you are using the Net Present Value (NPV) model as a basis for the evaluation of the alternatives. You are uncertain about the exact values of the NPV’s input variables. Therefore, there is a risk associated with your decision. Your objective (or goal) here is to make your decision knowing that there is uncertainty.”

You would like to maximise your profit, but you are willing to take some risk of losing money,

6. What do you think are the best two alternatives?

   1- ___________

   2- ___________

7. From among your best two alternatives, which alternative do you prefer the most? What factors would influence your choice between these two?

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8. How confident do you feel that you have made a well-informed choice about which alternative you prefer most?

Not confident at all	1	2	3	4	5	Very confident

9. If you discovered that the Discount Rate was likely to be at the higher end of the possible range, are there any circumstances that would make you change your mind about which of your best two alternatives you prefer?

   ____

   Why?

   ____

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   ____

   ____

10. How confident do you feel that you have made a well-informed choice about which alternative you would prefer most in question 9?

Not confident at all	1	2	3	4	5	Very confident

11. Do you feel that you have enough information to make an informed choice? If not then how could this be resolved so that you feel better informed?

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Any other comments about your decisions?

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The second version of the visualisation tool

Figure 2 shows the second version of the visualisation tool. Please read the description of the second version of the visualisation tool in Figure 2 and then complete the following tasks.

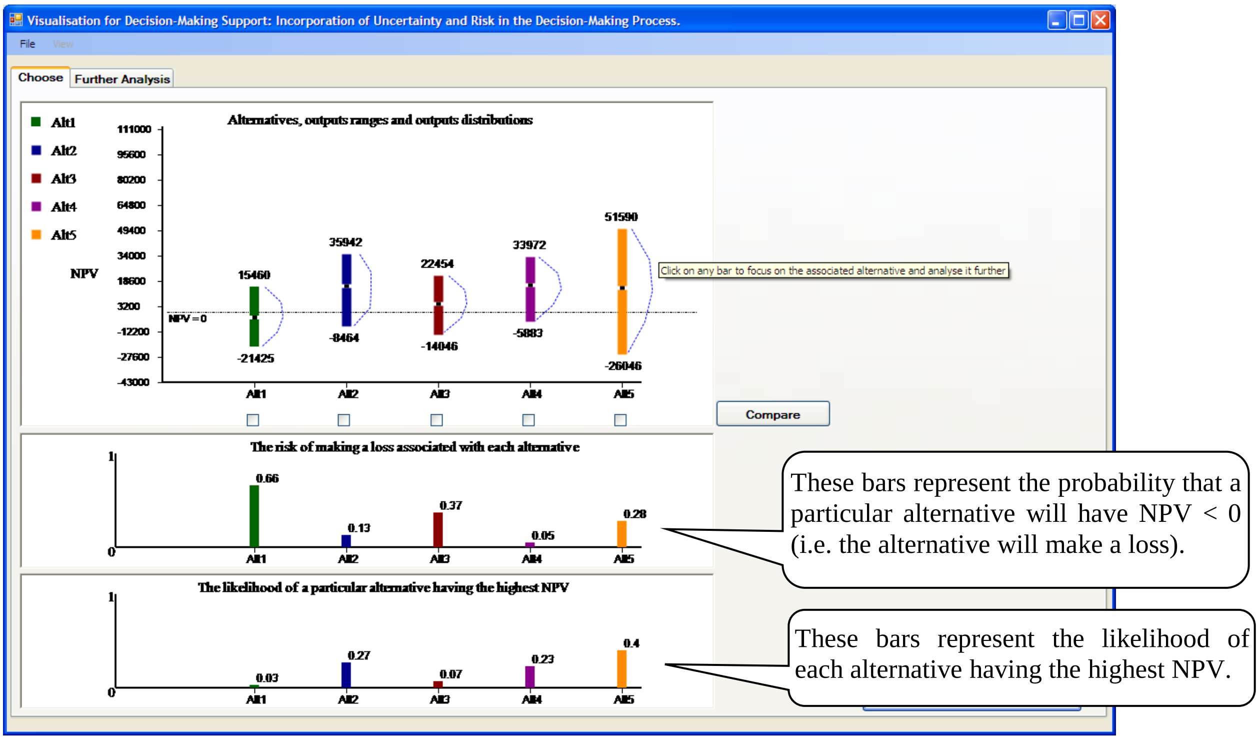

Figure 2: A screenshot of the second version of the visualisation tool.

Practice Tasks

1. The risk of making a loss for Alt5 compared to Alt2 is about?

☐ 3 times as much ☐ Twice as much ☐ The same ☐ About half as much ☐ About a third as much

2. What are the two most risky alternatives (i.e., alternatives that involve highest probabilities of NPV being less than zero)?

☐ Alt1 Alt5 ☐ Alt3 Alt4 ☐ Alt2 Alt4 ☐ Alt1 Alt3

3. How often would you expect Alt2 to have the highest return (i.e. highest NPV)?

☐ Never ☐ About ¼ of the time ☐ About ½ of the time ☐ About ¾ of the time ☐ Always

4. What are the two alternatives that have the greatest likelihood of having the highest NPV?

☐ Alt1 Alt3 ☐ Alt2 Alt4 ☐ Alt2 Alt5 ☐ Alt4 Alt5

Decision-Making Scenario:

Please read through the following scenario then complete the following tasks:

"Suppose you are planning to make an investment and you have five alternatives to choose from: Alt1, Alt2, Alt3, Alt4 and Alt5. Because they all involve the investment of dollars, you are using the Net Present Value (NPV) model as a basis for the evaluation of the alternatives. You are uncertain about the exact values of the NPV's input variables. Therefore, there is a risk associated with your decision. Your objective (or goal) here is to make your decision knowing that there is uncertainty."

You would like to maximise your profit, but you are willing to take some risk of losing money,

5. What do you think are the best two alternatives?

   1- ____________

   2- ____________

6. From among your best two alternatives, which alternative do you prefer the most? What factors would influence your choice between these two?

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7. How confident do you feel that you have made a well-informed choice about which alternative you prefer most?

Not confident at all	1	2	3	4	5	Very confident

8. If you discovered that the Discount Rate was likely to be at the higher end of the possible range are there any circumstances that would make you change your mind about which of your best two alternatives you prefer?

____

Why?

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9. How confident do you feel that you have made a well-informed choice about which alternative you would prefer most in question 8?

Not confident at all	1	2	3	4	5	Very confident

10. Do you feel that you have enough information to make an informed choice? If not then how could this be resolved so that you feel better informed?

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Any other comments about your decisions?

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The third version of the visualisation tool

Figures 3, 4 and 5 show screenshots of the third version of visualisation tool. Please read the description of the third version of the visualisation tool in Figures 3 and then complete the following tasks.

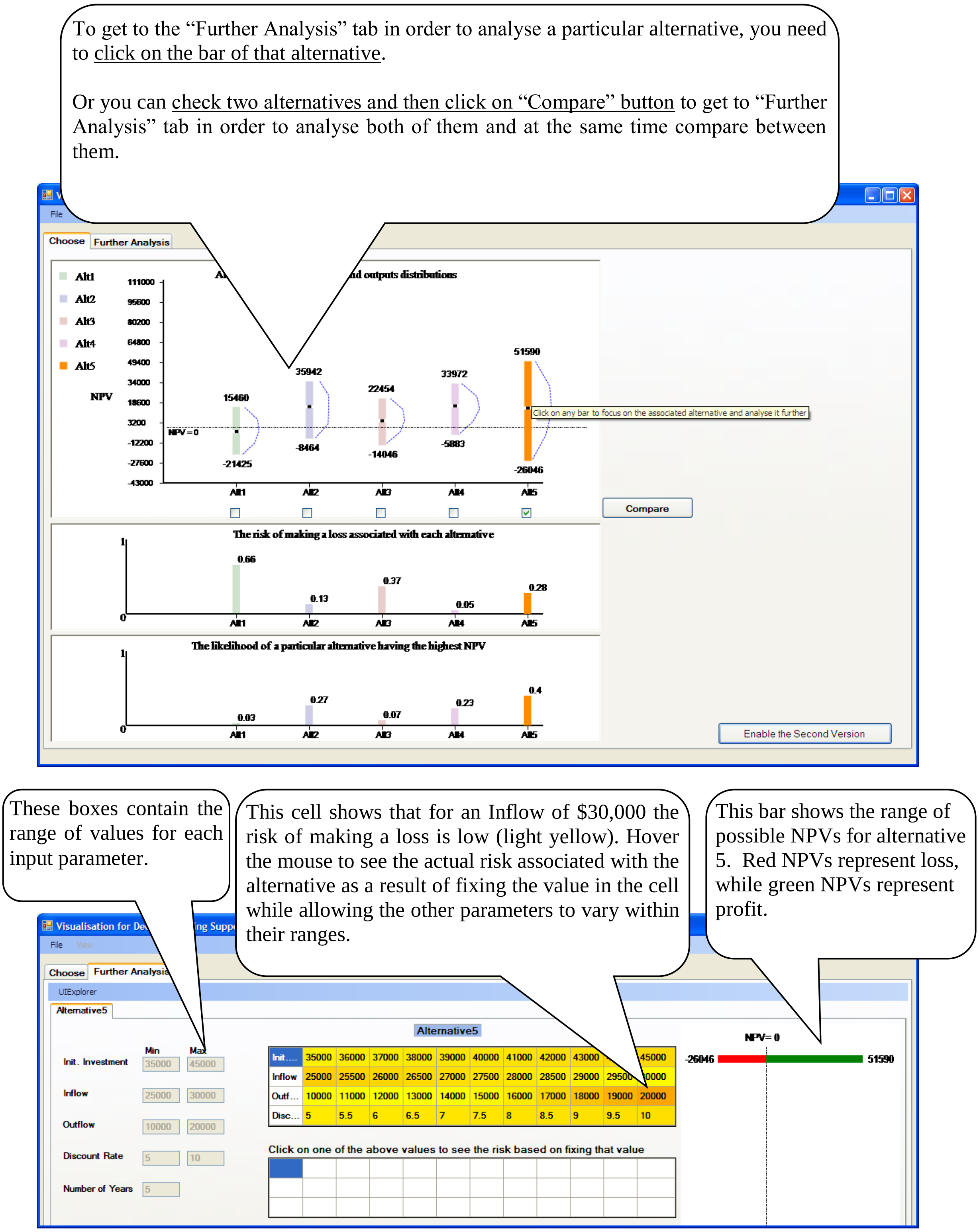

Figure 3: A screenshot of the "Further Analysis tab" at the third version of the visualisation tool.

Now click on the bar of Alt5 and complete the following tasks.

This shows more detailed information about Alt5 for different values of the input variables.

1. The colour of a cell shows the risk of making a loss associated with that value of the input variable.
2. As the colour changes from yellow to dark orange the risk of making a loss becomes greater. Yellow means no risk of making a loss (probability = 0), dark orange means high risk of making a loss.
3. You can retrieve the risk value by hovering the mouse over any of the cells.

Practice Tasks

1. Based on the displayed ranges of input variables, which variable do you think has the most effect on the risk of making a loss?

   ☐ Initial Investment ☐ Inflow ☐ Outflow ☐ Discount Rate

2. Based on the displayed ranges of NPV values (the red/green bars), approximately what proportion of the possible NPVs will make a loss?

   ☐ About 1/4 of the NPVs ☐ About 1/3 of the NPVs ☐ About 1/2 of the NPVs ☐ About 2/3 of the NPVs ☐ All NPVs

3. For what range of Cash Outflow values can you be assured that the NPV will stay>0 i.e. there is no risk of making a loss? (Other input variables can vary within their ranges).

☐ $10000 - $20000 ☐ $16000 - $20000 ☐ $13000 - $17000 ☐ $10000 - $13000

When you click a cell in the first grid (top grid), the value of the related variable will be fixed. As a result, another grid will appear showing the risk of making a loss (i.e. probability of making a loss) related to the values of the other input variables.

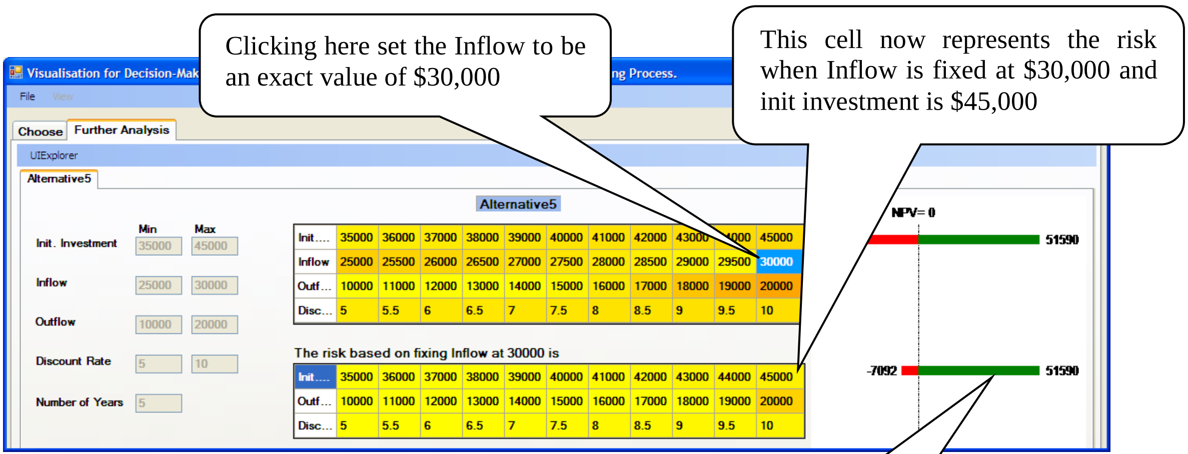

Figure 4: A screenshot of the "Further Analysis tab" at the [illegible] version of the visualisation tool.

Practice Tasks

4. Suppose that you have decided to make an Initial Investment of $35000, at what range of cash Inflow values can you be sure that the NPV will stay > 0 i.e. there is no risk of making a loss?

   ☐ $250000 - 30000 ☐ $25000 - $27800 ☐ $29500 - 30000 ☐ $27100 -$28500

5. Suppose that the Cash Inflows are expected to be $30000 each year, from the bottom red/green bar approximately what proportion of the possible NPVs will make a loss?

   ☐ About 15% of the NPVs ☐ About 30% of the NPVs ☐ About 50% of the NPVs ☐ About 80% of the NPVs ☐ All NPVs

6. Suppose you fixed the Initial Investment at $45000, Cash Inflow at $25000, and Cash Outflow at $14000, what is the range of Discount Rate that leads to a risk of making a loss less than or equal to 0.2?

   ☐ 5 – 6.5 ☐ 7.5 – 9.5 ☐ 5 - 10 ☐ 5 – 7.5

Instead of choosing one alternative for further analysis, you can choose two alternatives for further analysis and at the same time compare between them. For example, Figure 5 shows the "Further Analysis tab" after selecting the two alternatives (Alt2 and Alt5).

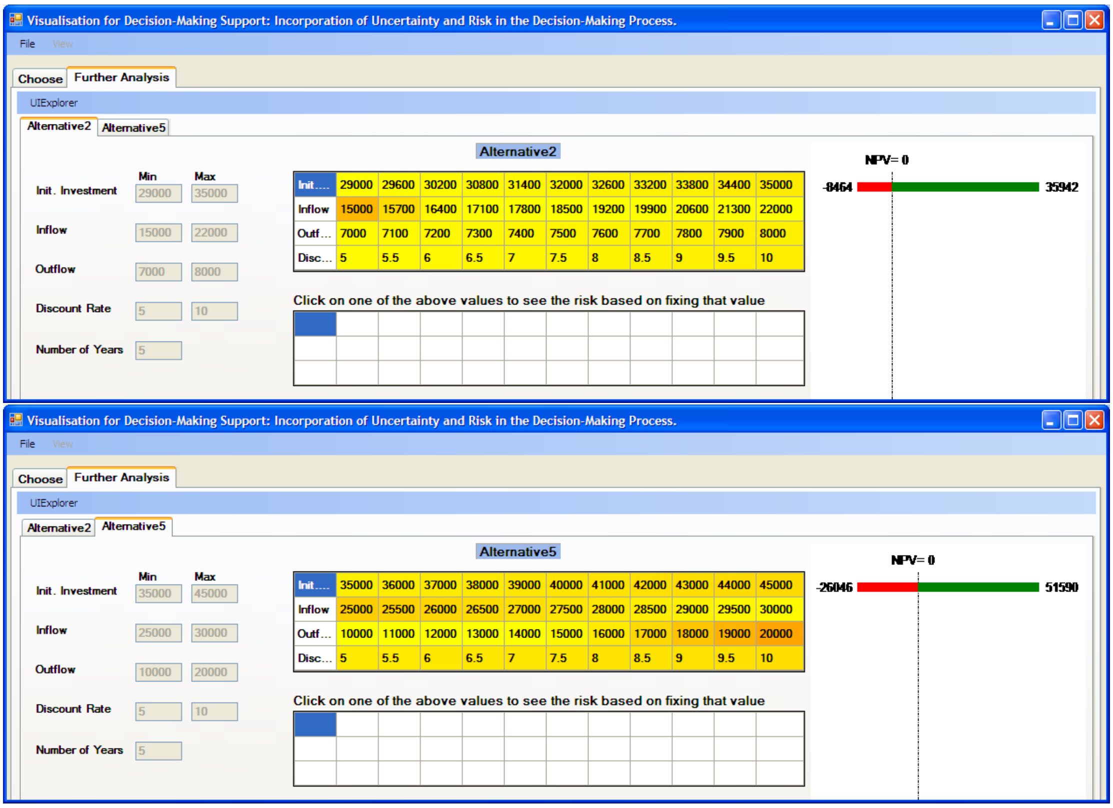

Figure 5: A screenshot of the "Further Analysis tab" when selecting Alt2 and Alt5 to compare between them.

Decision-Making Scenario:

Please read through the following scenario then complete the following tasks:

"Suppose you are planning to make an investment and you have five alternatives to choose from: Alt1, Alt2, Alt3, Alt4 and Alt5. Because they all involve the investment of dollars, you are using the Net Present Value (NPV) model as a basis for the evaluation of the alternatives. You are uncertain about the exact values of the NPV's input variables. Therefore, there is a risk associated with your decision. Your objective (or goal) here is to make your decision knowing that there is uncertainty."

You would like to maximise your profit, but you are willing to take some risk of losing money,

7. What do you think are the best two alternatives?

   1- ___________

   2- ___________

8. From among your best two alternatives, which alternative do you prefer the most? What factors would influence your choice between these two?

   ____

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9. How confident do you feel that you have made a well-informed choice about which alternative you prefer most?

Not confident at all	1	2	3	4	5	Very confident

10. If you discovered that the Discount Rate was likely to be at the higher end of the possible range are there any circumstances that would make you change your mind about which of your best two alternatives you prefer?

    ____

    Why?

    ____

    ____

    ____

    ____

11. How confident do you feel that you have made a well-informed choice about which alternative you would prefer most in question 9?

Not confident at all	1	2	3	4	5	Very confident

12. Do you feel that you have enough information to make an informed choice? If not then how could this be resolved so that you feel better informed?

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Any other comments about your decisions?

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B.2 Results of the evaluation study (Chapter 6)

The participants rate of experience (Where 1: First time, 2: Basic understanding, 3: Regularly practicing)

Participant	1. Financial information models	2. Decision-making under certainty	3. Decision-making under uncertainty and risk
P#1	3	3	3
P#2	2	2	2
P#3	2	2	2
P#4	1	1	1
P#5	2	2	2
P#6	2	2	1
P#7	2	2	2
P#8	1	2	1
P#9	2	2	2
P#10	2	2	2
P#11	3	1	1
P#12	2	1	1
Total of participants vs level of experience	**Financial information and models**	**Decision-making under certainty**	**Decision-making under uncertainty and risk**
Novice	3	5	5
Intermediate	6	6	6
Expert	3	1	1

The best two alternatives from the perspective of participants.			
Participant	**Outcome Bars**	**Risk and Likelihood Bars**	**Risk Explorer**
P#1	**Alt2**	**Alt4**	**Alt4**
	Alt4	**Alt2**	**Alt2**
P#2	**Alt4**	**Alt4**	**Alt4**
	Alt2	**Alt2**	**Alt2**
P#3	**Alt4**	**Alt4**	**Alt4**
	Alt2	**Alt2**	**Alt2**
P#4	**Alt4**	**Alt4**	**Alt4**
	Alt2	**Alt2**	**Alt2**
P#5	**Alt2**	**Alt2**	**Alt4**
	Alt4	**Alt4**	**Alt2**
P#6	**Alt5**	**Alt5**	**Alt2**
	Alt2	**Alt2**	**Alt4**
P#7	**Alt4**	**Alt4**	**Alt4**
	Alt2	**Alt2**	**Alt2**
P#8	**Alt2**	**Alt4**	**Alt4**
	Alt4	**Alt2**	**Alt2**
P#9	**Alt4**	**Alt4**	**Alt4**
	Alt2	**Alt2**	**Alt2**
P#10	**Alt2**	**Alt2**	**Alt4**
	Alt4	**Alt4**	**Alt2**
P#11	**Alt4**	**Alt2**	**Alt4**
	Alt2	**Alt4**	**Alt2**
P#12	**Alt4**	**Alt4**	**Alt4**
	Alt2	**Alt2**	**Alt2**

Frequency of ranking the two most preferred alternatives			
	Outcome Bars interface	**Risk and Likelihood bars interface**	**Risk Explorer interface**
Alt4 then Alt2	**8**	**9**	**11**
Alt2 then Alt4	**3**	**2**	**1**
Alt5 then Alt2	**1**	**1**	**0**

The most preferred alternative			
Participant	**Outcome Bars**	**Risk and Likelihood Bars**	**Risk Explorer**
P#1	**Alt 4**	**Alt 4**	**Alt 4**
p2	**Alt 4**	**Alt 4**	**Alt 4**
P#2	**Alt 4**	**Alt 4**	**Alt 4**
P4	**Alt 4**	**Alt 4**	**Alt 4**
P#3	**Alt 2**	**Alt 4**	**Alt 4**
P6	**Alt 5**	**Alt 5**	**Alt 2**
P#4	**Alt 4**	**Alt 4**	**Alt 4**
P8	**Alt 2**	**Alt 4**	**Alt 4**
P#5	**Alt 4**	**Alt 4**	**Alt 4**
P10	**Alt 2**	**Alt 2**	**Alt 4**
P#6	**Alt 4**	**Alt 4**	**Alt 4**
P12	**Alt 4**	**Alt 4**	**Alt 4**

Most preferred Alternative			
	Outcome Bars interface	**Risk and Likelihood bars interface**	**Risk Explorer interface**
Alt2	**3**	**1**	**1**
Alt4	**8**	**10**	**11**
Alt5	**1**	**1**	

Level of confidence using each interface (where 1 = "not confident at all", and 5 = "very confident)			
Participant	**Outcome Bars**	**Risk and Likelihood Bars**	**Risk Explorer**
P#1	4	5	3
P#2	4	4.5	5
P#3	3	4	5
P#4	4	4	5
P#5	5	5	5
P#6	5	5	5
P#7	5	3	5
P#8	4	4	5
P#9	4	4	2
P#10	4	4	4
P#11	3	3	4
P#12	4	4	5

	Average	stdev
Outcome Bars	4.08	0.67
Risk and Likelihood Bars	4.13	0.68
Risk Explorer	4.42	1.00

Adequacy of information provided (Yes/No)			
Participant	**Outcome Bars**	**Risk and Likelihood Bars**	**Risk Explorer**
P#1	**no**	**no**	**yes**
P#2	**no**	**no**	**yes**
P#3	**no**	**no**	**no**
P#4	**no**	**no**	**yes**
P#5	**yes**	**yes**	**yes**
P#6	**no**	**no**	**yes**
P#7	**no**	**no**	**yes**
P#8	**no**	**no**	**yes**
P#9	**no**	**no**	**yes**
P#10	**no**	**no**	**no**
P#11	**no**	**no**	**yes**
P#12	**no**	**no**	**yes**
	Outcome Bars	**Risk and Likelihood Bars**	**Risk Explorer**
Total (Sufficient information)	**1**	**1**	**10**
Total (Lack of enough information)	**11**	**11**	**2**

Types of information required			
	Outcome Bars	**Risk and Likelihood Bars**	**Risk Explorer**
Information about the input variables	**9**	**9**	**1**
Information about the decision context	**4**	**4**	**4**
Additional supporting information	**3**	**3**	**7**